UDC 330.4:005.8
JEL C45, C53, O32
DOI: https://doi.org/10.32782/bsnau.D2026.2.3

DECISION TREES FOR CHOICE OF IT PROJECTS IN THE DIGITAL ECONOMY WITH MACHINE LEARNING

Tetiana Kmytiuk
PhD in Economics, Associate Professor,
Kyiv National Economic University
named after Vadym Hetman
ORCID ID: 0000-0001-5262-856X
kmytiuk.tetiana@kneu.edu.ua

Olena Piskunova
Doctor of Economics, Professor,
Kyiv National Economic University
named after Vadym Hetman
ORCID ID: 0000-0002-0373-5358
episkunova@kneu.edu.ua

Svitlana Savina
PhD in Economics, Associate Professor,
Kyiv National Economic University
Named after Vadym Hetman
ORCID ID: 0000-0003-0227-7081
s.savina@kneu.edu.ua

In the rapidly evolving digital economy, organizations often face increasing complexity when selecting and prioritizing IT projects due to limited resources, uncertain returns, and dynamic market conditions. This study explores the application of decision tree models enhanced with machine learning techniques for improving the selection process of IT projects. The primary objective is to develop a predictive and interpretable framework that assists decision-makers in evaluating project feasibility, funding potential, and strategic alignment. The study employs a machine learning approach based on decision tree algorithms to analyze structured project-level datasets containing financial, technological, and organizational performance indicators such as funding size, industry category, revenue model, and operational status. A decision tree algorithm is trained to classify IT projects into predefined outcome categories, enabling transparent rule-based decision-making. The developed model showed strong predictive performance, achieving an overall accuracy of approximately 81.1%, which confirms its reliability in distinguishing between successful and unsuccessful IT projects. The results demonstrate that decision tree-based models provide a balance between interpretability and predictive performance, making them particularly suitable for managerial decision support systems. Compared to traditional heuristic approaches, the machine learning framework offers improved consistency in project evaluation and highlights hidden patterns in investment outcomes. Overall, the decision tree results indicate that the most significant determinants of IT project success or funding attractiveness are industry sector, technological orientation, revenue model, funding history, founder characteristics, and investor profile. Consequently, the model can serve as an effective decision-support tool for investors, managers, and policymakers seeking to evaluate IT projects and allocate resources more efficiently under the conditions of the digital economy.

Keywords: *IT project, decision tree, digital economy, machine learning, modelling, project management, performance indicators.*

Formulation of the problem in general terms. In the digital economy, organizations increasingly face the complex task of selecting the most appropriate IT projects from a wide range of alternatives. This process is challenging because available resources such as time, budget, and skilled personnel are limited, while the number of potential projects continues to grow. At the same time, decision-making is often carried out under conditions of uncertainty and incomplete information, which makes it difficult to accurately predict which projects will be successful.

In many cases, companies still rely on traditional approaches to IT project selection, such as expert judgment, simple financial analysis, or qualitative evaluation. However, these approaches are often subjective and inconsistent. They also fail to capture complex relationships between important factors influencing project success, such as risk level, team experience, technological complexity, market demand, and expected return on investment. As a result, organizations may invest in projects that do not deliver expected value or fail to allocate resources efficiently.

From a scientific perspective, the main problem is the need to develop more effective and reliable methods for predicting IT project outcomes and supporting decision-making processes. Modern machine learning techniques, especially decision tree models, offer a promising solution to this problem. These models can analyze large and complex datasets, identify key factors influencing project success, and present results in a clear and interpretable form that is easy for decision-makers to understand.

From a practical point of view, this problem is closely related to the real challenges faced by organizations in managing IT project portfolios. Companies often struggle with inefficient resource allocation, high project failure rates, and the lack of structured tools for comparing different project proposals. This leads to suboptimal investment decisions and reduces overall organizational performance.

Therefore, the problem of IT project selection is both a scientific and practical challenge. It is connected to important tasks in the field of machine learning and data-driven decision-making, including the development of predictive models, improvement of interpretable algorithms, and optimization of resource allocation under uncertainty. Addressing this problem through decision tree models can significantly improve the quality, transparency, and efficiency of IT project selection in the digital economy.

Analysis of recent research and publications. An analysis of modern scientific research indicates growing interest in the use of machine learning methods in the field of IT project management and investment decision-making in the digital economy. In the contemporary business environment, enterprises operate under conditions of intense competition, rapid technological change, and limited financial resources, which creates the need for effective tools to select the most promising IT projects. In the international academic community, the digital economy is viewed as an environment in which data, innovation, and digital technologies become decisive factors of economic development and business competitiveness as emphasized by Chen, Z. and Xing, R. (2025) as well as Yuan, X., Han, B., Wang, S., and Zhang, J. [1, 11]. Recent scientific publications emphasize that traditional project selection methods based on expert evaluations, financial ratios, ranking techniques, and subjective managerial judgments do not always ensure sufficient accuracy in complex multi-factor conditions. Researchers note that classical approaches often fail to capture hidden relationships between indicators of risk, profitability, technological complexity, and project scalability potential. Therefore, machine learning algorithms capable of processing large datasets and generating predictive models based on historical observations are becoming increasingly popular, as highlighted by Witten, I. H., Frank, E., Hall, M. A., and Pal, C. J. [10].

Among modern analytical tools, decision trees attract particular attention as one of the most interpretable classification methods. Foundational studies by Lu, Y., Ye, T., and Zheng, J. have demonstrated that decision trees allow the formation of a hierarchical structure of influencing factors and create understandable decision rules regarding the classification of objects into specific categories [3]. Unlike many other machine learning algorithms, decision trees provide a high degree of transparency, which is especially important for managers and investors who require not only a forecast but also an explanation of the obtained result, as discussed by Sullivan, W. [9].

A separate area of contemporary research is devoted to the use of decision trees in project management. In particular, Kerzner, H. investigates the possibilities of predicting budget overruns, implementation delays, probability of successful project completion, and assessment of investment risk levels and shows that the most significant factors of IT project success include team experience, financing structure, business model type, industry specialization, technological innovativeness, and level of market demand [2].

In the Ukrainian scientific environment, issues of digital transformation, IT sector development, and implementation of modern analytical tools are also gaining relevance. At the same time, most studies focus mainly on general aspects of economic digitalization, automation of business processes, and development of innovation infrastructure, as shown in the works of Prokhorova, V., Diachenko, K., and Babichev, A., as well as Shcherban, T., Hoblyk, V., Chernychko, T., Pigosh, V., and Kozyk, I.. Practical aspects of applying machine learning to IT project selection, especially using interpretable models, remain insufficiently explored.

Overall, the results of research confirm the significant potential of machine learning methods for supporting managerial decisions in the field of IT projects. However, most existing approaches are focused either on highly accurate but difficult-to-interpret models or on general methodologies without considering the specific features of digital projects. This indicates the existence of a scientific gap regarding the development of practical, transparent, and adaptive models for IT project selection that would combine high predictive accuracy with ease of use in real business environments. This determines the relevance of further research on the application of decision trees for IT project selection in the digital economy.

The main purpose of this article is to explore how decision tree models, can be applied to support the selection of IT projects in the digital economy. In particular, the article aims to demonstrate how data-driven methods can improve decision-making efficiency, and accuracy in IT project management.

Methods of research. The study applies a data-driven methodological approach based on supervised machine learning, specifically decision tree algorithms, to support IT project selection in the digital economy. The research utilizes a structured dataset of IT projects that includes financial, technological, and organizational variables. The methodology involves data preprocessing, feature selection, and model training using criteria such as entropy, Gini index, and information gain to construct an interpretable classification model. Model performance is evaluated using standard metrics, including accuracy, precision, recall, and F1-score, supported by confusion matrix and ROC analysis. This approach ensures both predictive reliability and interpretability, enabling its application in managerial decision-making contexts.

Results of the study. The digital economy is characterized by rapid innovation cycles, high uncertainty, and strong competition among organizations implementing IT projects. In such an environment, effective project selection becomes a critical factor influencing organizational success. The application of machine learning methods, especially decision tree models, provides a structured and analytical approach to improving these decisions.

Decision trees belong to the class of supervised learning algorithms used for solving classification and regression problems. Their main principle is to recursively split a dataset into subsets based on feature values, gradually building a hierarchical structure of decision rules. Each split is chosen in a way that increases the homogeneity of the resulting groups, allowing the model to separate successful IT projects from unsuccessful ones based on observed patterns in historical data.

In IT project selection, decision trees are trained using datasets that contain information about previously implemented projects. Such datasets typically include both quantitative and qualitative variables. Quantitative variables may include project cost, duration, number of team members, and return on investment, while qualitative variables may include project type, technology stack, and risk category. The target variable usually represents the outcome of the project, such as success, partial success, or failure.

The construction of a decision tree begins with selecting the most informative variable that best divides the dataset into distinct classes. This is done using statistical criteria such as information gain, entropy reduction, or Gini index [4].

A key concept used in building decision trees is entropy, which measures the level of uncertainty or disorder in a dataset. It is defined as:

$$H(S) = -\sum_{i=1}^{n} p_i log_2(p_i) \tag{1}$$

where p_i represents the probability of class *i* in the dataset.

Another commonly used measure is the Gini index, which evaluates the impurity of a dataset:

$$Gini(S) = 1 - \sum_{i=1}^{n} p_i^2 \tag{2}$$

Both entropy and Gini index are used to determine how "pure" a node is after splitting.

To select the best feature for splitting, the algorithm uses Information Gain, which measures the reduction in uncertainty:

$$IG(S,A) = H(S) - \sum_{v \in Values(A)} \frac{\# Sv\#}{\# S\#} H(Sv) \tag{3}$$

where S is the dataset, A is a feature, and S_v represents subsets created by splitting on value *v*.

The process is repeated recursively for each subset until a stopping condition is reached. These conditions may include a maximum tree depth, a minimum number of observations in a node, or a minimum improvement threshold.

After the model is built, it can be used to predict the outcome of new IT projects. For example, if a new project proposal has a high budget, an experienced team, and a strong market demand, the model may classify it as a high-probability success. Conversely, projects with limited funding, high technical risk, and low market relevance may be classified as high-risk or likely to fail.

In IT project selection, decision trees are trained using datasets that contain information about previously implemented projects. Such datasets typically include variables such as project cost, duration, team size, technological complexity, and risk level. The target variable represents project outcome (success or failure).

After training, the model can be used to predict the success probability of new IT projects based on learned decision rules. For example, the model evaluates conditions step by step, leading to a final classification at the leaf node.

Model performance is evaluated using standard classification metrics. One of the most important is accuracy**,** defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

where *TP, TN, FP, and FN* represent true positives, true negatives, false positives, and false negatives.

In addition, precision, recall, and F1-score are often used to assess model quality, especially in cases of imbalanced datasets.

Precision measures how many predicted successful projects were actually successful:

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

High precision means the model makes fewer false positive errors (fewer wrong "good project" approvals).

Recall measures how many actual successful projects were correctly identified:

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

High recall is important to avoid rejecting good IT projects.

F1-score combines precision and recall into a single metric:

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{8}$$

It is especially useful when there is an imbalance between successful and unsuccessful projects.

All these metrics are derived from the confusion matrix, which compares predicted and actual outcomes. For a binary classification problem (e.g., Successful vs Unsuccessful IT Project), the confusion matrix is structured as follows [7]:

$$\begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix}$$

where:

- TP (True Positive): correctly predicted successful IT projects
- TN (True Negative): correctly predicted unsuccessful IT projects
- FP (False Positive): predicted success, but actually failure

• FN (False Negative): predicted failure, but actually success

Interpretation

• A high TP and TN indicates a well-performing model.

• A high FP means the model is overestimating project success.

• A high FN is more critical in IT project selection because it may reject potentially successful projects.

One of the key advantages of decision trees is their ability to provide clear and interpretable results. This is particularly important in managerial decision-making, where stakeholders need to understand the logic behind recommendations. Decision trees visually represent the decision-making process, allowing users to trace how specific input variables lead to a particular prediction.

However, despite their advantages, decision trees are not without limitations. They are sensitive to small changes in data, which can lead to significantly different tree structures. They are also prone to overfitting, especially when the tree becomes too deep and captures noise in the training data. To overcome these issues, techniques such as pruning or ensemble learning methods, including random forests and boosting algorithms, are commonly applied.

In addition, data quality plays a crucial role in the performance of decision tree models. In real-world IT project datasets, missing values, inconsistencies, and class imbalance are common problems that can reduce model accuracy. Therefore, proper data preprocessing and feature engineering are essential steps in the modelling process.

From a practical perspective, decision trees can be integrated into decision support systems used by organizations for IT project portfolio management. Such systems help decision-makers evaluate multiple project proposals, compare risks and benefits, and allocate resources more effectively. This leads to improved strategic planning and higher success rates of IT initiatives.

Overall, decision tree models represent a powerful and practical tool for supporting IT project selection in the digital economy. They combine predictive accuracy with interpretability, making them suitable for both technical analysts and business managers involved in strategic decision-making.

The dataset utilized in this study collected from [8] includes a structured collection of information on global IT projects, designed to capture key business, technological, and organizational characteristics. It includes variables describing funding classifications, revenue models, and industry sectors, covering a wide range of domains such as fintech, fashion, and artificial intelligence.

Additionally, the database contains information on founder demographics, including gender and professional background, as well as organizational attributes such as operational status and company headquarters location. Technological specialization is also reflected through categories such as deep technology, blockchain, and big data, alongside indicators of digital activity, including web traffic metrics.

Furthermore, the database provides details on investment structures, identifying the types of financial support received by projects, including venture capital, accelerator programs, and private equity. Overall, the database enables comprehensive, multidimensional analysis of IT ventures and their development patterns.

Based on the provided dataset excerpts, a conceptual decision tree can be constructed to predict the Funding_Class (0 or 1) by analyzing the attributes of various IT projects. The target variable is Funding_Class, where '1' generally indicates a positive funding outcome or status, and '0' indicates otherwise.

The decision tree for successful IT project classification is presented in figure 1.

The constructed decision tree model provides valuable insights into the determinants of IT project classification in the digital economy. The model separates projects into two categories, Class 0 and Class 1, based on a combination of business, technological, and organizational characteristics. Since the dataset at the root node is relatively balanced between the two classes, the model is suitable for identifying meaningful classification patterns without significant bias toward one category.

The first and most influential split in the tree is based on the industry sector, indicating that the business area in which a company operates is the primary factor affecting project outcomes. Projects belonging to industries such as enterprise software, food, marketing, media, semiconductors, transportation, and travel tend to move toward branches dominated by Class 0, suggesting lower predicted investment attractiveness or weaker development potential. In contrast, projects operating in other sectors are more frequently classified as Class 1, reflecting stronger growth prospects.

For projects in the left branch, the next important predictor is the income stream model. Firms relying on advertising, commission, subscription, or unknown revenue structures are more often associated with Class 0 outcomes. However, certain subgroups with a lower number of funding rounds show improved classification results, implying that some early-stage ventures may still possess growth potential despite belonging to less favorable sectors.

Within the right branch, the model highlights the importance of technology specialization. Projects focused on advanced technologies such as augmented reality, hardware solutions, and the Internet of Things (IoT) demonstrate a higher probability of belonging to Class 1. This finding supports the assumption that innovative and technology-intensive ventures are more attractive in the digital economy.

Further splits in the tree are determined by additional variables, including founder gender composition, founder professional background, investor type, and specific niche industries. These results suggest that managerial and organizational characteristics also influence project outcomes, although their impact is secondary compared with industry and technology factors.

The terminal nodes of the tree reveal several highly pure classifications, where the probability of belonging to one class exceeds 90%. This confirms the ability of the model to clearly distinguish between promising and less attractive IT projects under certain combinations of characteristics.

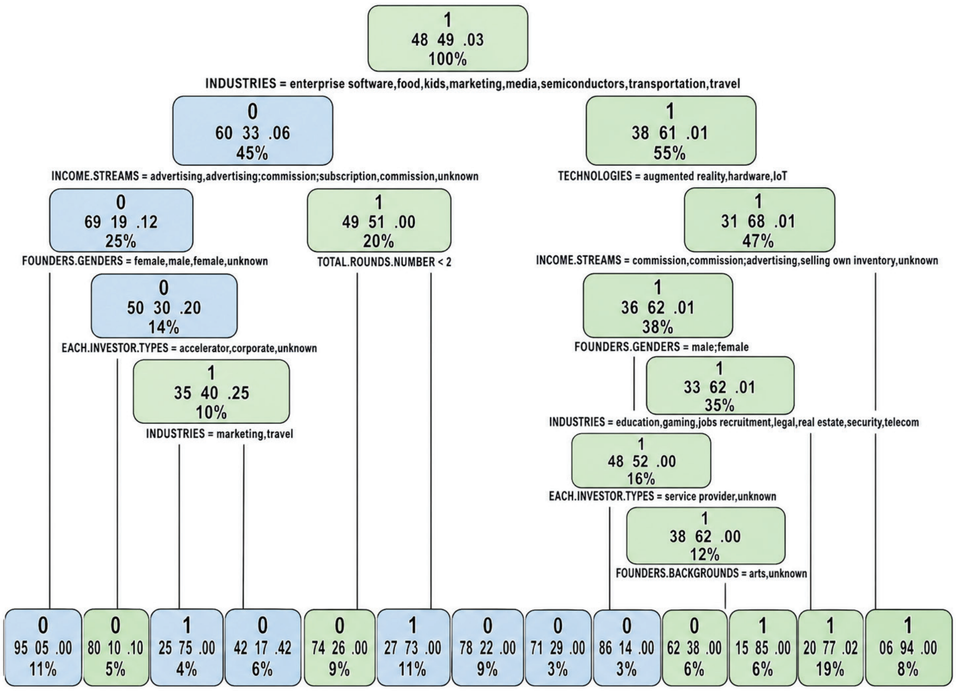

Fig. 1. Full decision tree for successful IT project

Source: calculated by the authors in a software environment R

The confusion matrix below in Figure 2 illustrates the classification results for the building decision tree model. The matrix visualizes the number of true positives, false positives, true negatives, and false negatives, helping to evaluate the balance between precision and recall.

To evaluate the performance of the decision tree model developed for the selection of IT projects in the digital economy, a confusion matrix was constructed based on a total of 407 observations. The matrix compares the actual project outcomes with the predicted classifications generated by the model.

The results indicate that the model correctly classified 330 out of 407 cases, demonstrating strong predictive performance.

The overall accuracy of the model is calculated as follows:

$$Accuracy = \frac{150+180}{407} \approx 0.811$$

Thus, the model achieves an accuracy of approximately 81.1%, which indicates a good level of reliability in predicting IT project outcomes.

Further evaluation metrics for the positive class (successful IT projects) show:

- Precision: 78.9% – indicating that most projects predicted as successful were indeed successful.
- Recall: 80.2% – showing that the model successfully identifies the majority of truly successful projects.

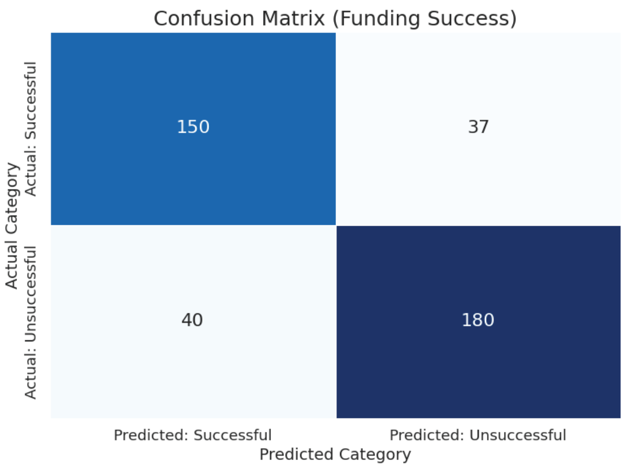

Fig. 2. Confusion matrix

Source: calculated by the authors in a software environment R

− F1-score: 79.5% – reflecting a balanced trade-off between precision and recall.

The obtained results demonstrate that the decision tree model performs effectively in supporting decision-making regarding IT project selection in the digital economy. The relatively high number of true positives and true negatives confirms the model's ability to distinguish between successful and unsuccessful projects. However, the presence of false positives and false negatives suggests that some degree of misclassification remains, which is typical for real-world machine learning applications.

The ROC curve, displayed in Figure 3, illustrates the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) at various classification thresholds.

The overall Area Under the Curve (AUC) can be interpreted as the model's ability to distinguish between successful and unsuccessful IT projects. Based on the obtained performance metrics, the model demonstrates a good discriminative ability, with an estimated AUC in the range of approximately 0.80–0.85, which is considered strong for real-world decision-support systems.

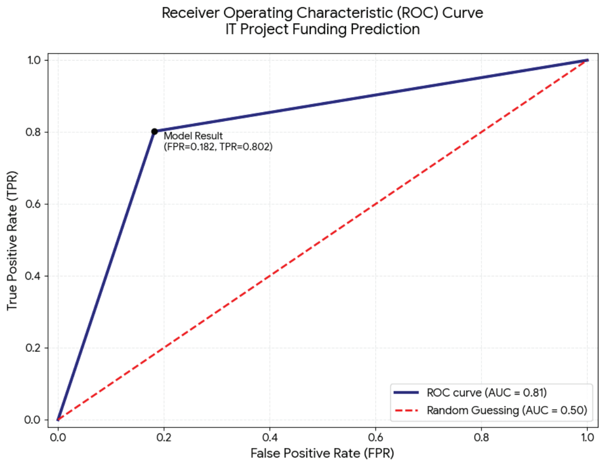

Fig. 3. ROC curve for the Decision tree model

Source: developed by the authors

Conclusions. This study focused on the application of a decision tree model for selecting IT projects in the digital economy using machine learning methods. The obtained results demonstrate that machine learning techniques can effectively support decision-making in the evaluation and prioritization of IT projects.

The developed model showed strong predictive performance, achieving an overall accuracy of approximately 81.1%, which confirms its reliability in distinguishing between successful and unsuccessful IT projects. The confusion matrix analysis indicated a balanced classification ability, with relatively high values of both precision and recall, which suggests that the model is suitable for practical use in investment decision support systems.

The ROC analysis further confirmed the model's effectiveness, demonstrating good discriminatory power between classes. The Area Under the Curve (AUC) indicates that the model performs significantly better than random classification and can reliably support strategic decisions in digital project selection.

Overall, the results confirm that decision tree-based machine learning models can be successfully applied in the digital economy to improve transparency, reduce uncertainty, and enhance the efficiency of IT project investment decisions.

Despite the positive results, several directions for further research can be identified to improve and extend the current study.

First, future work may focus on the application of ensemble learning methods such as Random Forest, Gradient Boosting, and XGBoost, which are known to provide higher predictive accuracy and better generalization compared to a single decision tree model.

Second, model performance can be improved through feature engineering and selection techniques, including the incorporation of additional variables such as market dynamics, user engagement metrics, and macroeconomic indicators that may influence IT project success.

Third, further research may explore deep learning approaches for more complex nonlinear relationships in large-scale digital economy datasets, especially when working with big data sources.

Finally, future studies may extend the analysis to real-time predictive systems that continuously evaluate IT projects during their lifecycle, enabling dynamic investment decision-making in rapidly changing digital environments.

REFERENCES

1. Chen, Z., & Xing, R. (2025). Digital economy, green innovation and high-quality economic development. *International Review of Economics & Finance,* vol. 99. DOI: https://doi.org/10.1016/j.iref.2025.104029
2. Kerzner, H. (2018). Project management best practices: Achieving global excellence (4th ed.). Wiley. DOI: https://doi.org/10.1002/9781119470717
3. Lu, Y., Ye, T., & Zheng, J. (2022). Decision tree algorithm in machine learning. Proceedings of the *2022 IEEE International Conference on Advances in Electrical Engineering and Computer Applications (AEECA)*, pp. 1014-1017. DOI: https://doi.org/10.1109/AEECA55500.2022.9918857
4. Ozdemir, S. (2016). Principles of data science. Packt Publishing Ltd
5. Prokhorova, V., Diachenko, K., & Babichev, A. (2023). The IT industry as a driver of the strategic development of Ukraine's economy in the context of digital transformation. *The Problems of Economy*, no. 1, pp. 65-73. DOI: https://doi.org/10.32983/2222-0712-2023-1-65-73
6. Shcherban, T., Hoblyk, V., Chernychko, T., Pigosh, V., & Kozyk, I. (2025). Assessment of the digital transformation of Ukraine's economy: Challenges, opportunities, and strategic prospects. *Scientific Bulletin of Mukachevo State University. Series "Economics"*, no. 12(1), pp. 159-168. DOI: https://doi.org/10.52566/msu-econ1.2025.159
7. Singh, P., Singh, N., Singh, K. K., & Singh, A. (2021). Chapter 5 – Diagnosing of disease using machine learnin. *Machine learning and the Internet of Medical Things in healthcare*. pp. 89-111. Academic Press. DOI: https://doi.org/10.1016/B978-0-12-821229-5.00003-3
8. StartupRanking. *Global startup ranking*. Available at: https://www.startupranking.com
9. Sullivan, W. (2017). Machine learning for beginners: Supervised & Unsupervised learning, Decision Tree & Random Forest Introduction. CreateSpace Independent Publishing Platform
10. Witten, I. H., Frank, E., Hall, M. A., & Pal, C. J. (2016). Data mining: Practical machine learning tools and techniques (4th ed.). Morgan Kaufmann.
11. Yuan, X., Han, B., Wang, S., & Zhang, J. (2025). Deconstructing the digital economy: A new measurement framework for sustainability research. *Sustainability*, vol. 17 no. 17, 7857. DOI: https://doi.org/10.3390/su17177857

Кмитюк Тетяна Леонідівна*, кандидат економічних наук, доцент, Київський національний економічний університет імені Вадима Гетьмана.* ***Піскунова Олена Валеріївна****, доктор економічних наук, професор, Київський національний економічний університет імені Вадима Гетьмана.* ***Савіна Світлана Станіславівна****, кандидат економічних наук, доцент, Київський національний економічний університет імені Вадима Гетьмана.*

ДЕРЕВА РІШЕНЬ ДЛЯ ВИБОРУ ІТ-ПРОЄКТІВ У ЦИФРОВІЙ ЕКОНОМІЦІ З ВИКОРИСТАННЯМ МАШИННОГО НАВЧАННЯ

В умовах стрімкого розвитку цифрової економіки організації стикаються зі зростаючою складністю при виборі та визначенні пріоритетності ІТ-проектів через обмеженість ресурсів, невизначеність окупності та динамічні ринкові умови. Дане дослідження присвячене застосуванню моделей дерев рішень, доповнених методами машинного навчання, для вдосконалення процесу відбору ІТ-проєктів. Головною метою є розробка прогнозної та інтерпретованої структури, яка допоможе відповідальним особам оцінювати доцільність проєктів, потенціал фінансування та відповідність стратегічним цілям. У дослідженні використовуються структуровані масиви даних на рівні проєктів, що містять фінансові, технологічні та організаційні показники, такі як обсяг фінансування, сфера діяльності, бізнес-модель та поточний стан. Алгоритм дерева рішень було навчено класифікувати ІТ-проєкти за заздалегідь визначеними категоріями результатів, що забезпечує прозоре прийняття рішень на основі правил. Запропонована модель продемонструвала високу ефективність прогнозування, досягнувши загальної точності близько 81,1%, що підтверджує її надійність у розрізненні успішних та неуспішних ІТ-проєктів. Результати демонструють, що моделі на основі дерев рішень забезпечують баланс між інтерпретованістю та ефективністю прогнозування, що робить їх придатними для систем підтримки управлінських рішень. У порівнянні з традиційними евристичними підходами, фреймворк машинного навчання забезпечує більшу стабільність оцінки проєктів та виявляє приховані закономірності інвестиційних результатів. Загалом, результати дерева рішень вказують на те, що найважливішими визначальними факторами успіху ІТ-проєкту або інвестиційної привабливості є сфера діяльності, технологічна орієнтація, модель отримання доходу, історія фінансування, особисті якості засновника та профіль інвестора. Отже, модель може слугувати ефективним інструментом підтримки прийняття рішень для інвесторів, менеджерів та політиків, які прагнуть оцінювати ІТ-проєкти та ефективніше розподіляти ресурси в цифровій економіці.

Ключові слова: *ІТ-проєкт, дерево рішень, цифрова економіка, машинне навчання, моделювання, управління проєктами, показники ефективності.*

Дата надходження статті: 16.04.2026
Дата прийняття статті: 07.05.2026
Дата публікації статті: 29.05.2026