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DECISION SUPPORT SYSTEM FOR PROJECT RESOURCE PLANNING BASED ON THE RANDOM FOREST METHOD

The study develops and justifies the structure of a decision support system (DSS) designed to automate project resource planning processes using the Random Forest method. The relevance of the research is driven by the necessity to transition from subjective estimates to analytical tools for forecasting project costs and duration. The proposed system architecture covers the full data processing cycle: from automated input data collection from corporate databases (such as Jira or MS Project) to the generation of visual reports for management. Implementing the Random Forest algorithm within the DSS framework enables the identification of critical project parameters, specifically technical complexity and external risks, directly at the initiation and planning stages. Special emphasis is placed on the development and implementation of a feature importance visualization mechanism, which transforms the forecasting model into a transparent analytical tool. This allows managers to not only obtain predicted values but also understand the underlying structure of the factors influencing them. It was established that the feature hierarchy, where technical complexity plays a leading role (0.793), enables the project manager to focus on the most critical planning nodes. Such an approach significantly enhances the transparency of decision-making and fosters increased stakeholder trust in the system's recommendations. The practical significance of the results lies in the possibility of implementing predictive management methods. The system identifies potential project bottlenecks before actual difficulties arise, providing the manager with a basis for timely reviews of team composition, budget limit adjustments, or schedule modifications. Thus, the proposed DSS serves as an effective tool for active management, providing decision support to prevent cost overruns and project schedule delays in dynamic environments.

Keywords: decision support system (DSS), project resource planning, Random Forest, feature importance, predictive management, technical complexity, risk identification, management automation.

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СИСТЕМА ПІДТРИМКИ ПРИЙНЯТТЯ РІШЕНЬ У ПЛАНУВАННІ РЕСУРСІВ ПРОЄКТІВ НА ОСНОВІ МЕТОДУ RANDOM FOREST

У роботі розроблено та обґрунтовано структуру системи підтримки прийняття рішень (СППР), призначеної для автоматизації процесів планування ресурсів проєктів на основі методу Random Forest. Актуальність дослідження зумовлена необхідністю переходу від суб'єктивних оцінок до використання аналітичних інструментів при прогнозуванні витрат і тривалості проєктів. Запропонована архітектура системи охоплює повний цикл обробки даних: від автоматизованого збору вхідної інформації з корпоративних баз даних (таких як Jira або MS Project) до формування візуальних звітів для менеджменту. Застосування алгоритму Random Forest у межах СППР дозволяє здійснювати ідентифікацію критичних параметрів проєкту, зокрема технічної складності та зовнішніх ризиків, безпосередньо на етапах його ініціації та планування. Особливу увагу в дослідженні приділено розробці та реалізації механізму візуалізації важливості ознак (Feature Importance), що трансформує модель прогнозування на прозорий аналітичний інструмент. Це дозволяє менеджеру не просто отримувати прогнозовані значення, а й бачити структуру чинників, що на них впливають. Встановлено, що ієрархія ознак, де провідну роль відіграє показник технічної складності (0,793), дозволяє керівнику проєкту зосередити увагу на найбільш критичних елементах плану. Такий підхід суттєво підвищує рівень прозорості прийняття рішень та сприяє зростанню довіри до рекомендацій системи з боку стейкхолдерів.Практичне значення отриманих результатів полягає у можливості впровадження методів випереджального управління. Система дозволяє ідентифікувати потенційні «вузькі місця» проєкту ще до появи реальних труднощів, надаючи менеджеру базу для вчасного перегляду складу команди, коригування бюджетних лімітів або графіків виконання робіт. Таким чином, запропонована СППР стає ефективним інструментом активного управління, який забезпечує підтримку прийняття рішень для запобігання перевищенню витрат і зриву термінів реалізації проєктів у динамічних умовах.

Ключові слова: система підтримки прийняття рішень, планування ресурсів проєкту, Random Forest, важливість ознак, випереджальне управління, технічна складність, ідентифікація ризиків, автоматизація управління.

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Introduction

Resource planning is a fundamental process in project management, encompassing the estimation of human, financial, material, and temporal requirements. Traditional methodologies, largely reliant on expert judgment and historical precedents, frequently struggle to identify latent patterns and the intricate interdependencies among diverse influencing factors. Resources constitute a critical project constraint, and the efficiency of their utilization fundamentally dictates the success of project implementation. The relevance of this research is underscored by the growing need for organizations to minimize costs, enhance forecasting precision, mitigate resource scarcity, and streamline inventory and logistics. Ineffective resource management inevitably results in direct financial attrition, excessive inventory overheads, production schedule disruptions, and a decline in customer service quality. Intelligent resource management allows for a shift from static planning to adaptive, data-driven strategies, which is important for dynamic and multi-project environments. The use of machine learning within decision support systems and corporate information systems increases the practical value of this study. This integration enables the automated analysis of resource allocation scenarios, helps to reduce the impact of subjective human factors, and improves the reliability of management decisions.

Therefore, given the increasing complexity of projects and higher demands on management efficiency, there is a need for a decision support system (DSS) that uses intelligent data analysis methods.

Related works

Traditional approaches to project resource planning, based on expert judgment, deterministic models, or static rules, often lack flexibility under conditions of uncertainty, dynamic environmental changes, and resource constraints.

The use of machine learning methods in resource planning allows for the analysis of large volumes of historical data, identifying hidden patterns and forecasting resource needs with higher accuracy [1, 2]. This is particularly relevant for projects in fields such as information technology, construction, energy, logistics, and finance, where planning errors can lead to significant budget overruns, missed deadlines, and reduced quality of results [3, 4].

Modern machine learning methods, including decision trees, Random Forest, gradient boosting, and neural networks, provide adaptability to planning models by allowing systems to automatically update forecasts during project execution [5, 6]. This facilitates a transition from static planning to intelligent real-time resource management, which is a key component of the digital project management concept.

The authors of [7] investigated existing project automation tools capable of developing project schedules with estimations of total duration, budget, and tracking capabilities. However, a significant gap remains regarding the assessment of whether a specific resource possesses the necessary competence and expertise for effective task execution. To address this deficiency, the researchers propose a model for predicting resource fitment using machine learning based on a game-theoretic approach. Training datasets processed with SVM classifiers achieved an accuracy level of approximately 97%, demonstrating the model's effectiveness.

In [8], an approach is proposed for constructing a hybrid intelligent system that integrates artificial intelligence, big data analytics, agent-based modeling, and agile project management methodologies. The study focuses on adapting the system to dynamic environmental changes and the high level of uncertainty inherent in modern IT projects. The authors introduce algorithms designed to support effective decision-making under time constraints, changing customer requirements, and technical complexity. Simulation results indicate that the developed system reduces software project risks by 22% and improves the accuracy of planning and optimal decision selection by 18%.

Article [9] presents a methodology for managing closed-loop supply chains (CLSC) using a decision support system based on fuzzy logic and machine learning. The system provides operational solutions for manufacturing plants integrated into a CLSC to achieve production goals despite inherent uncertainties. A key advantage of the proposed approach is its ability to mitigate the impact of imbalances in other chain links on raw material and finished goods inventories. To achieve this, an intelligent algorithm monitors plant operations and reschedules tasks to ensure process objectives are met. The tool is developed by combining fuzzy logic techniques with machine learning methods.

The authors of [10] analyzed state-of-the-art machine learning methods applicable as decision support systems for estimating resource consumption in the construction of reinforced and prestressed concrete road bridges. The study examined the application of artificial neural networks (ANN), regression trees (RT), support vector machines (SVM), and Gaussian process regression (GPR). The accuracy of each model was determined through a multi-criteria evaluation based on four metrics: root mean square error (RMSE), mean absolute error (MAE), Pearson’s linear correlation coefficient (R), and mean absolute percentage error (MAPE). According to all established criteria, the GPR-based model demonstrated the highest accuracy in calculating concrete consumption. The research suggests that utilizing automatic relevance determination (ARD) covariance functions yields the most precise and optimal models, while also providing insights into the relative importance of each input variable to the model's overall accuracy.

Article [11] proposes a decision support system for R&D budget allocation designed to maximize the total expected R&D output. The system incorporates an R&D outcome prediction model integrated with an optimization technique. Initially, a machine learning algorithm is utilized to accurately estimate future outcomes. Subsequently, an optimization technique is applied to hedge against uncertainty in the predicted values. This approach enables the effective development of a budget allocation plan.

Analysis of modern research shows that significant attention is paid to the use of machine learning and intelligent decision support systems in resource management. This includes assessing resource fitment, forecasting consumption, budget planning, and adapting to uncertainty. However, most existing approaches either focus on specific management aspects (such as competence fit, individual resource estimation, or budgeting) or are characterized by high model complexity and limited practical usability for project managers.

Despite the progress in these studies, there is still a lack of user-friendly decision support systems that combine the accuracy of machine learning with a clear practical algorithm for managers working in constantly changing environments.

Purpose

The aim of this article is to improve the validity and efficiency of project resource planning by implementing a decision support system (DSS) based on the Random Forest machine learning method. The study focuses on formalizing resource planning as a predictive task, analyzing the structural organization of the DSS, and evaluating the Random Forest method's capability to forecast key resource metrics and project risk levels. This approach aims to reduce the manager's workload and enhance the overall efficiency of the planning process under conditions of uncertainty.

Formalization of the project resource planning problem as a predictive task

Project resource management is a complex, multi-factor process that requires accounting for numerous parameters characterizing both the project itself and its implementation conditions. Within the framework of modern project management, the resource planning problem can be interpreted as a predictive task aimed at obtaining quantitative and qualitative assessments of the project's future state based on its current and initial characteristics.

From the perspective of decision theory, resource planning involves determining the expected volume of required resources, estimating the probability of budget overruns, and forecasting the risk of schedule delays. Each of these aspects is critical for the project manager, as they directly influence the selection of implementation strategies, the allocation of human and financial resources, and the formulation of corrective management actions when deviations occur.

The formalization of this problem is based on the assumption that a functional dependency exists between the set of project characteristics and resource efficiency indicators. In a general form, this dependency can be represented as follows (1):

$$f:\ X \to Y \qquad (1)$$

where f - objective function;

X - the set of project input characteristics;

Y - the set of output indicators to be predicted.

The project characteristic vector X is formed from parameters available during the planning phase or at the early stages of project execution. These parameters include planned task duration, project complexity level, number of involved team members, their qualification levels, project type, planned scope of work, prior experience in similar projects, as well as organizational and external factors. The combination of these features forms a high-dimensional space where individual parameters may exhibit complex non-linear interdependencies.

The input characteristic vector is represented as follows (2):

$$X = (x_1, x_2, \ldots, x_n) \qquad (2)$$

where each component x corresponds to an individual project characteristic available at the planning stage or in the early phases of its execution.

The set of input indicators may include the following parameters

- temporal parameters including the planned duration of the project and its stages;
- organizational parameters containing parameters such as the number of team members team structure and their qualification level;
- complexity indicators including the scope of work level of novelty and technological intensity;
- financial characteristics such as the planned budget and cost structure;
- categorical features such as project type industry and work organization model;
- external factors including the level of environmental uncertainty and organizational constraints.

The specified parameters form a high-dimensional space where complex non-linear relationships may exist between individual features. The set of output values Y is defined by the problem statement:

- in the regression setting – the predicted volume of financial or human resources expected budget overruns and deviation from planned deadlines;
- in the classification setting – the project risk class such as low medium or high.

The set of output values Y reflects the target indicators of resource planning. Depending on the problem statement, they can be both numerical and categorical. In the case of a regression setting, the output variables can be the predicted volume of human or financial resources, expected costs, or the magnitude of deviation from planned values. In a classification setting, the output can be the project risk class, such as low, medium, or high risk of budget overruns or schedule delays.

A specific feature of the resource planning problem is that the dependency between X and Y usually cannot be adequately described by linear or analytical models. Real-world projects are characterized by a high level of uncertainty, the presence of hidden factors, and interdependencies that are difficult to formalize using traditional methods. Therefore, it is appropriate to use machine learning methods capable of automatically identifying patterns in large arrays of historical data.

In this context, the resource forecasting task effectively reduces to training a model f based on a sample of historical projects for which both input characteristics and actual implementation results are known. Once trained, the model allows for a new project with given parameters X to obtain predicted values Y, which can serve as a basis for supporting managerial decision-making.

The effectiveness of solving the forecasting problem largely depends on the correct formation of the input feature vector X, which should reflect the project's specifics and implementation conditions as comprehensively as possible. In project resource planning tasks, input parameters typically have different natures, scales, and levels of impact on the final result, necessitating their systematization and preliminary analysis.

The input vector X is formed based on characteristics available during the planning stage or at the early phases of the project lifecycle. These characteristics include temporal parameters, such as the planned duration of the project and its individual stages, organizational parameters related to the number of performers and team structure and complexity indicators reflecting the scope of work, level of novelty, or technological intensity of the project. Financial parameters, including the planned budget, cost structure, and resource constraints, also play a crucial role.

Rationale for selecting the Random Forest method in forecasting model development

Selecting the machine learning algorithm to implement the mapping $f: X \to Y$ is a key stage in building a decision support system. In project resource planning tasks, the model must meet several requirements, including the ability to work with high-dimensional data, account for non-linear dependencies, remain robust to noise, and provide sufficient forecasting accuracy.

The comparative analysis of forecasting methods was conducted based on four key criteria: model interpretability, data volume requirements, the risk of overfitting, and implementation complexity within the manager's workflow. (Tab.1).

Table 1

Comparative characteristics of the methods

Criteria	Random Forest	Linear Regression	Neural Networks
Interpretability	High	High	Low
Data volume requirements	Low	Moderate	High
Risk of overfitting	Low	Low	High
Implementation complexity	Low	Moderate	High

The Random Forest method satisfies these requirements due to its ensemble nature. It is based on constructing a multitude of decision trees, each trained on a random subset of data and features. The final decision is formed by aggregating the results of individual trees, which reduces the impact of random errors and enhances the model's generalization capability.

In the context of the resource planning problem, Random Forest can be used for both regression and classification settings. In the regression case, the model allows for predicting numerical indicators, such as the volume of required resources or the magnitude of potential budget overruns. In the classification setting, the algorithm can be applied to categorize projects into specific risk classes, such as low, medium, or high.

A significant advantage of Random Forest is the ability to estimate feature importance, which allows for the interpretation of modeling results. For a project manager, this means not only obtaining a forecast but also understanding which specific project characteristics have the greatest impact on risks and resource volume. Such interpretability is a crucial factor when implementing decision support systems into practical activities.

Furthermore, Random Forest is resistant to overfitting, which is particularly important when historical project data is limited. By utilizing random subsamples and an ensemble approach, the model maintains the ability to adequately generalize information and demonstrate stable results on new data.

Thus, the application of the Random Forest method as an implementation of function f in the project resource planning problem is justified both in terms of forecasting accuracy and the practical suitability of the results for supporting managerial decisions.

Decision support system architecture for project resource planning

Developing a decision support system for project resource planning based on the Random Forest method requires a clear structural organization that ensures a complete data lifecycle from collection to the formulation of managerial recommendations. The proposed system is designed to use historical and current project data and is integrated into the project management process as an analytical tool to support managerial decision-making.

The overall structure of the system is based on a modular principle, which allows for the separation of functional components according to the stages of information processing while ensuring the flexibility and scalability of the solution. The structural diagram of the decision support system is presented in Fig. 1.

The central element of the system is the decision support subsystem, which consists of a data preprocessing module, a feature vector formation module, the Random Forest method, and an output indicator generator. This subsystem implements the mapping f: X → Y based on the Random Forest algorithm; however, its effective operation is impossible without preliminary data preparation and the subsequent interpretation of results.

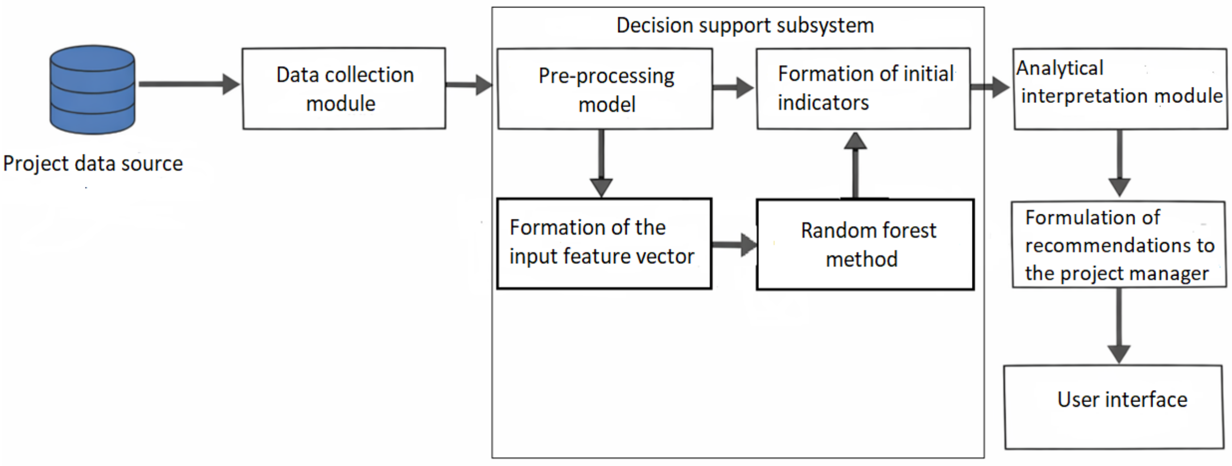

Fig.1. The structure of the decision support system for project resource planning

At the first stage of the system's operation, input data is collected from project management information systems, corporate databases, or external sources. These data contain information about project parameters, their progress, and actual resource utilization. A significant feature of this stage is the ability to work with incomplete or heterogeneous data, which is typical for real-world project management conditions.

The next structural component is the data preprocessing module, which prepares the information for use in the machine learning model. At this stage, operations such as data cleaning, handling missing values, normalizing numerical features, and converting categorical parameters into numerical form are performed. The correct operation of this module is critically important, as the quality of the input vector X directly impacts the forecasting accuracy.

Upon completion of data preparation, the formed input vector is passed to the machine learning module, which implements the Random Forest algorithm. This module is responsible for training the model on historical data and generating forecasts for new or ongoing projects. Depending on the task, the model can operate in regression mode, predicting numerical resource utilization indicators, or in classification mode, determining the risk level of budget overruns or schedule delays.

An essential element of the system's structure is the analytical interpretation module, which transforms the model's output into a format understandable to the user. At this stage, predicted values are analyzed, risk levels are assessed, and the key factors influencing the obtained results are identified. Utilizing the feature importance estimation mechanisms in Random Forest ensures the transparency of the decisions made and increases the project manager's trust in the system.

The final component of the system is the user interface, which facilitates interaction between the decision support system and the decision-maker. Through this interface, the project manager accesses forecasts, analytical reports, and resource planning recommendations. This allows the modeling results to be used not merely as formal numerical estimates, but as a practical tool for adjusting plans and selecting optimal management strategies.

Thus, the proposed structure of the decision support system provides a holistic approach to project resource planning by combining machine learning methods with classical management principles. Integrating the Random Forest algorithm into such a system enables a transition from intuitive decisions to data-driven forecasts, which is particularly relevant in the context of increasing project complexity and resource constraints.

Experiments

To conduct experimental research, open datasets were utilized, specifically data from the NASA PROMISE repository and other publicly available datasets for project resource estimation within the context of resource and duration forecasting tasks [12, 13]. The PROMISE repository contains software engineering project data collected from numerous real-world NASA projects and converted into a format that facilitates repeatable machine learning experiments.

The proposed decision support system is designed for practical use by project managers during the planning and execution control phases. At the start of the workflow, the manager inputs the core parameters of a new project into the system. These include planned deadlines, budget volume, the number of specialists in the team, and their qualification levels. It is also essential to specify the project type and its technical complexity level. The system provides the capability for automated data extraction from corporate software (such as Jira or MS Project), which significantly streamlines the process and reduces manual input errors.

After the data is entered, the system automatically:

1. Forms the input feature vector.
2. Applies the trained Random Forest model.
3. Generates predicted values:

– expected volume of actual costs;
– probability of budget overrun;
– risk class for schedule delays.

Once the data is collected, the system launches the Random Forest algorithm. The model analyzes the input parameters and compares them with the experience of past projects. As a result, the manager receives a clear forecast (Fig.2):

– the actual cost of work, which may differ from the planned cost;
– the risk of exceeding the budget in percentage terms;
– the probability of project completion delay.

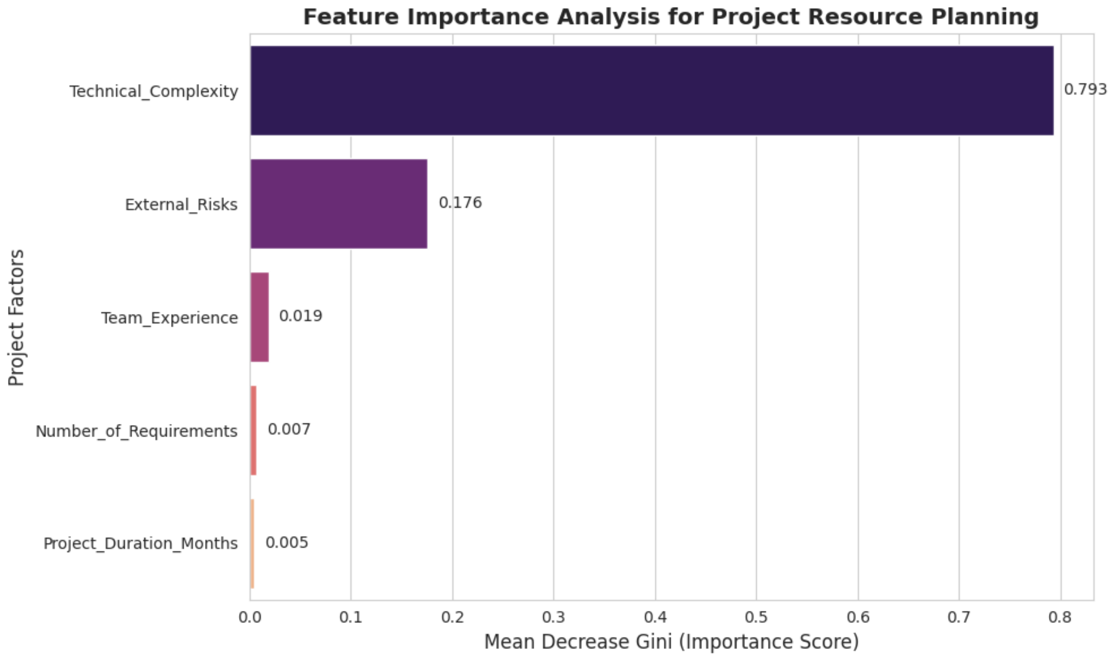

Fig.2. Evaluation of project factor influence on resource planning results

The analysis of the relative importance of project factors, as presented in Fig. 1, provides insights into the internal logic of the forecasting model. The importance score is calculated based on the Mean decrease Gini [10], which measures how much each feature contributes to the homogeneity of the nodes in the underlying decision trees.

The results indicate a highly skewed distribution of influence among the parameters:

1. Technical complexity (0.793) is the dominant factor, accounting for nearly 80% of the model's predictive power. This suggests that the inherent difficulty and novelty of the project are the primary drivers of resource consumption and risk.
2. External risks (0.176) hold secondary importance. This confirms that while internal project parameters are crucial, environmental uncertainty significantly impacts the stability of resource planning.
3. Team experience (0.019), number of requirements (0.007), and project duration (0.005) show surprisingly low direct influence within the tested dataset.

From a managerial perspective, this hierarchy suggests that to improve the accuracy of resource estimates, the primary focus should be on the objective assessment of technical complexity and the identification of external threats, rather than solely on temporal or quantitative metrics.

As a result of the decision support system's operation, the manager receives not only numerical forecasts but also analytical explanations, such as:

– key factors that influenced the forecast;
– feature importance rankings (e.g., budget, number of performers, complexity);

– visual indicators of risk levels.

This enables the assessment of potential problem causes even before the project execution begins. Consequently, the manager can make informed managerial decisions, such as adjusting the budget or schedule, changing the team composition or size, allocating additional reserves, or selecting an alternative project implementation strategy.

Thus, the system serves as a proactive management tool rather than merely a means of recording factual deviations.

Conclusions

In the course of the study, the structure of a decision support system for project resource planning based on the Random Forest method was developed and justified. The use of the Random Forest model ensures the identification of critical risks, such as technical complexity or external factors, as early as the planning stage. Through the visualization of feature importance, managers obtain objective data for the timely adjustment of budgets and schedules. This enables a transition from merely recording deviations to preventing them, minimizing the likelihood of schedule delays and cost overruns. The identified hierarchy of factors, where technical complexity has a dominant influence (0.793), allows the manager to focus on critical planning nodes and significantly increases stakeholder trust in the system's recommendations.

The practical significance of the results lies in the possibility of transitioning from intuitive to data-driven management, where the leader can act predictively. A key advantage of the system is that it does not merely output numbers but explains their underlying basis. The manager sees a clear chart indicating which specific factors had the greatest impact on the forecast. For instance, the system may suggest that the primary threat to the schedule is the technical complexity of the task rather than a lack of personnel. This allows the leader to identify project vulnerabilities before they escalate into actual problems. With such a forecast at hand, the manager can act ahead of time. If the system indicates a high risk, the team composition can be reviewed in advance, the reserve fund increased, or the work schedule modified. Thus, the proposed DSS becomes a tool for active management, allowing not just for the recording of problems but for their timely prevention.

Author Contributions

Hnatchuk Yelyzaveta – conceptualization, methodology, formal analysis, supervision, and final editing of the manuscript.

Lebedovska Mariia – data curation, software implementation (Random Forest), experimental testing, writing original draft preparation, and visualization.

Declaration on the use of generative artificial intelligence tools

In the preparation of this work, the authors used ChatGPT and Grammarly for grammar and spelling checks, paraphrasing, and rephrasing of individual sentences. After using these tools/services, the authors reviewed and edited the content and take full responsibility for the content of this publication.

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