



Research Article

Development of a data-driven model based on machine learning for screening urban infrastructure projects considering sustainability and agility dimensions

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Abstract

This study aims to advance the evaluation and screening process of urban infrastructure projects by designing a data-driven classification model based on the CatBoost machine learning algorithm. The proposed model classifies projects into three decision categories—Selected, Reserved, and Rejected—using 13 indicators derived from two integrated dimensions: sustainability (with its economic, social, and environmental sub-dimensions) and agility. The dataset comprises 380 real-world projects, each annotated with corresponding indicator values and expert-labeled final decisions. A rigorous statistical analysis was conducted to confirm data quality, balance, and absence of multicollinearity. Subsequently, the CatBoost model was trained and optimized via hyperparameter tuning and cross-validation techniques. Its classification performance was benchmarked against Support Vector Machine (SVM) and Artificial Neural Network (ANN) models. Results revealed the superiority of CatBoost, which achieved an accuracy of 91.21% and an F1-score of 90.32%, outperforming both alternative models across all key metrics including precision and recall. Confusion matrix analysis further highlighted its robustness in correctly identifying projects in each of the three categories. The study demonstrates that advanced machine learning models—particularly those optimized for mixed-type and nonlinear datasets—can significantly improve multi-criteria decision-making processes in urban project management. The model's capability to integrate sustainability and agility perspectives offers a novel approach to address the complexities of modern infrastructure planning, especially in dynamic and data-rich environments. From a practical perspective, the proposed model supports urban policymakers, planners, and evaluators in selecting high-impact, future-ready projects. Theoretically, the research contributes to bridging the gap between strategic planning paradigms and intelligent computational tools. Future developments may explore integration with GIS data, real-time analytics, and adaptive learning features to expand applicability across urban development domains.

Keywords:

Project Selection;
Data-Driven Model;
Machine Learning;
Sustainability;
Agility

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1. Introduction

In today's fast-paced and complex world, a significant portion of human and organizational activities is defined and implemented in the form of projects. From technological development to environmental interventions, and from social programs to economic plans, the project-based approach has become the dominant paradigm for achieving strategic objectives (Zarjou & Khalilzadeh, 2022). Among these projects, urban infrastructure initiatives hold a special place, as they directly impact the quality of urban life, economic productivity, environmental sustainability, and social cohesion (Yeh & Chen, 2020; Zeynali et al., 2025). Given the scale, complexity, and long-term consequences of this category of projects, it is essential to design their evaluation and prioritization frameworks in a precise and scientific manner.

Infrastructure project evaluation—particularly in the field of urban development—has traditionally been based on a limited set of economic and financial indicators such as Return on Investment (ROI), Benefit-Cost Ratio, Net Present Value (NPV), and Payback Period. Although these indicators provide important insights, they are inadequate for the multidimensional analysis of urban development projects in the 21st century. In practice, many projects that score highly within traditional frameworks may not align with broader social goals or may lack the required long-term sustainability. As a result, relying solely on traditional criteria may lead to suboptimal decisions and misallocation of resources, especially in the public sector (Lee et al., 2020; Tavakoli et al., 2024).

To overcome these limitations, modern project evaluation frameworks increasingly incorporate the dimensions of sustainability and agility. These two paradigms reflect the fundamental characteristics of contemporary infrastructure projects and ensure that projects are evaluated not only from an economic perspective but also in terms of environmental responsibility, social inclusion, and adaptive capacity (Nessari et al., 2024). Over the past two decades, the concept of sustainability has become a core pillar in infrastructure planning and evaluation. Broadly defined, sustainability refers to the ability to meet present needs without compromising the ability of future generations to meet theirs and encompasses three main dimensions: environmental, social, and economic (Sharma & Joshi, 2023; Tajally et al., 2025). In the context of urban infrastructure, sustainable development requires balancing growth with resource conservation. Projects should be evaluated not only based on immediate efficiency but also on long-term environmental impacts, their contribution to social equity, and alignment with climate resilience goals (GhanavatiNejad et al., 2025; Mohagheghi & Mousavi, 2021; Sazvar et al., 2022). Indicators such as carbon emissions, resource efficiency, waste management, stakeholder participation, and lifecycle costs are among the key criteria for measuring project sustainability. Integrating these indicators into the project selection process facilitates cities' transition toward inclusive and green development.

In contrast, agility refers to the ability of systems, organizations, or projects to respond quickly and effectively to change (Sharma et al., 2022). In an era marked by uncertainty, disruption, and rapid shifts in

demand, urban infrastructure must be designed with the necessary flexibility, adaptability, and resilience. Agility in project management includes rapid decision-making, iterative development, modular design, and responsiveness to stakeholder feedback (Molaei et al., 2025; Rostami et al., 2023). In infrastructure projects, agility can manifest through adaptive construction methods, scalable systems, probabilistic planning, and smart technology integration. Project agility is assessed using indicators such as time-to-operation, modularity of design, risk responsiveness, stakeholder engagement, and operational flexibility. Projects that score higher in this area perform more effectively in dynamic urban environments (Gertzen et al., 2022; Javan-Molaei et al., 2024).

Despite the growing importance of sustainability and agility, operationalizing these concepts in project screening systems still faces challenges. Many existing evaluation frameworks are either too generic or static in nature and lack the adaptability required for complex and changing urban projects. Moreover, traditional decision-making tools often underperform when faced with multi-criteria and non-linear data. With the rise of smart cities and the growing availability of big data, there is a new opportunity to leverage advanced analytical methods to enhance the quality of project evaluation systems. In this context, data-driven approaches and machine learning models play a pivotal role. Unlike static scoring methods or subjective judgments, machine learning can process large volumes of data, identify hidden patterns, adapt to new information, and generate predictive insights (ForouzeshNejad, 2024; Nessari et al., 2024). By training on historical project data, stakeholder preferences, and contextual variables, these algorithms can perform project screening with greater accuracy, consistency, and transparency. Especially in complex, multi-criteria, and dynamic settings, such models outperform traditional ones and enable continuous learning and improvement (Kettunen & Lejeune, 2022; Zeynali et al., 2024). In this study, machine learning is considered not merely a computational tool but a novel paradigm for rethinking infrastructure project evaluation.

Accordingly, the aim of this research is to develop a data-driven screening model for urban infrastructure projects that integrates the dimensions of sustainability and agility in a unified manner. The proposed model employs supervised machine learning techniques to classify and rank projects based on historical and contextual data, incorporating indicators aligned with environmental, social, and adaptive performance. This model seeks to bridge the gap between theoretical frameworks and practical screening processes and to offer an innovative tool for urban policymakers.

In the following, Section 2. Literature review is presented, which reviews the related literature and identifies the research gap. Section 3. Methodology is written, and Section 4. Case Study and Evaluation Criteria is provided. Section 5. Findings is reported, Section 6 presents managerial insights and Section 7. Conclusion is presented.

2. Literature review

This section provides a concise review and analysis of studies related to project evaluation. For example, (Mahmoudi et al., 2021) proposed a comprehensive framework for large-scale multi-criteria decision-making

in the presence of incomplete data. They used the PCA method to cluster criteria and the K-means algorithm to cluster alternatives, thereby structuring the decision-making process. Then, fuzzy TOPSIS and the Ordinal Priority Approach (OPA) were applied to rank the clusters. A case study was conducted at a refinery equipment manufacturing company, and the results indicated high accuracy, flexibility, and efficiency of the proposed data-driven method under incomplete data conditions. Similarly, (Yang et al., 2022) proposed an optimized method for project site selection using an improved genetic algorithm. They collected and integrated spatial data and designed evaluation indicators to build the site selection framework. The algorithm was improved by focusing on eigenvalue enhancement and correlation factor optimization. Experimental results showed that the method achieved high compatibility with target projects (90–100%) and user satisfaction (95–99%), confirming its robustness.

(Namazi et al., 2023) also presented a strategic approach for R&D project portfolio selection using efficiency–uncertainty maps. Their goal was to align project portfolios with organizational mission and vision by leveraging expert knowledge. In their method, projects are mapped into four strategic zones (Exploitation, Challenge, Desperation, Discretion) to facilitate simultaneous analysis of strategic perspective and quantitative data. This helps decision-makers align portfolios with organizational goals. (Hong et al., 2023) proposed a multi-objective mean–semivariance model for project selection under uncertainty, incorporating reinvestment and synergy effects. Investment and profit were modeled as uncertain variables, aiming to maximize expected NPV and minimize risk. They introduced binary versions of Jaya and Rao algorithms, with binMORao2 showing the best performance across various test cases. The model effectively captures uncertainty and inter-project synergy, offering robust solutions for complex selection problems. In another study, (Kandakoglu et al., 2024) conducted a comprehensive literature review on the application of multi-criteria decision-making (MCDA) methods in project portfolio selection. They analyzed standalone and hybrid uses of MCDA with other modeling techniques, especially mathematical programming under resource constraints. The study identified weaknesses in hybrid approaches, discussed recent advances, and proposed a decision tree to guide researchers in selecting appropriate methods, along with suggestions for future research.

(Dağistanlı, 2024) introduced a VIKOR-based method in an Interval-Valued Intuitionistic Fuzzy (IVIF) environment for selecting R&D projects in the defense industry. The objective was to use MCDA techniques under uncertainty and incorporate expert opinion. In this study, eight criteria and four alternative projects were identified and evaluated by three decision-makers. Results showed that the VIKOR method in the IVIF environment provided both accuracy and consistency, and its application in the defense sector was considered innovative. Likewise, (Nessari et al., 2024) presented a data-driven model for evaluating and selecting projects based on criteria of resilience, circular economy, and Industry 4.0. The study began by identifying 21 indicators weighted using the FBWM method, followed by data labeling via WFIS.

Finally, a predictive model was developed using the LightGBM algorithm, achieving over 93% accuracy. The most important indicators were identified as "increasing market share via Industry 4.0 technologies" and "net present value." (ForouzeshNejad, 2024) proposed a hybrid data-driven framework for project portfolio selection in the telecommunication industry, incorporating both sustainability and strategic dimensions. The study began by identifying key evaluation criteria through literature review and expert input, and then weighted them using the Fuzzy Best–Worst Method (FBWM). The most critical criteria included initial capital requirements, initial revenue, number of specialists employed, energy consumption reduction, and market share growth. Using Data Envelopment Analysis (DEA), project performance was assessed annually, and the results were labeled to train machine learning models. Among the tested algorithms, the random forest regressor outperformed support vector regressors, achieving superior predictive accuracy in both training and testing phases. The findings highlight the effectiveness of integrating FBWM, DEA, and machine learning for data-driven and forward-looking project selection. (Bai et al., 2025) proposed a mathematical model for project portfolio selection and scheduling that incorporates dynamic synergy. The model aims to maximize project portfolio benefits with a balanced consideration of financial and non-financial factors, based on the Balanced Scorecard. Synergy benefits evolve over time and were quantified using system dynamics. The case study showed that the proposed model helps managers identify optimal projects and determine appropriate implementation timelines based on dynamic synergies. (Farahmand-Mehr & Mousavi, 2025) investigated resource-constrained multi-project scheduling problems (RCMPSP) under uncertainty caused by time-dependent reliability of renewable resources. They developed a new discrete-time binary integer programming model that incorporates variable failure and constant repair rates of resources over time. To solve this complex NP-hard problem, the authors proposed a Hybrid Immune Genetic Algorithm with Local Search (HIGALS), which features novel encoding, initialization, and search mechanisms. The algorithm was validated through a case study, where its performance was benchmarked against GAMS and six conventional algorithms. Results demonstrated that HIGALS achieved an average makespan reduction of over 11.79%, confirming its superiority in handling large-scale, uncertain scheduling environments.

The literature review shows that although many studies have applied MCDA methods, optimization models, and machine learning to project selection, most focus on areas like R&D, defense, or industry—failing to address the specific complexities of urban infrastructure. These studies often lack an integrated approach that considers both sustainability and agility, or they rely on theoretical models and synthetic data, limiting their practical value. The main research gap lies in the absence of a comprehensive, data-driven model tailored to urban infrastructure projects—one that simultaneously accounts for economic, environmental, social, and agility indicators using real-world data. This study addresses the gap by proposing a CatBoost-based classification model capable of handling mixed-type data

and delivering accurate, practical, and multi-level project screening

3. Methodology

In this study, the CatBoost algorithm has been utilized as a decision tree-based machine learning model to develop a data-driven screening model for the classification of urban infrastructure projects. CatBoost (Categorical Boosting) is one of the most powerful implementations of gradient boosting, specifically designed for datasets containing categorical features, and is capable of processing them effectively without manual encoding (Ghanavatinejad et al., 2019; Qian et al., 2023). CatBoost performs well when dealing with heterogeneous and multi-purpose data and, compared to other boosting algorithms such as XGBoost and LightGBM, offers greater stability, resistance to overfitting, and the ability to learn complex feature interactions (Rastgoo & Khajavi, 2023).

The CatBoost algorithm generally follows the steps below (Dutta & Roy, 2022; Zeynali et al., 2025):

- Automatic preprocessing of categorical features: Without the need for One-Hot Encoding or Label Encoding, the algorithm handles categorical features internally.
- Ordered Boosting: To prevent overfitting, the data is ordered such that future information does not leak into training phases.
- Sequential decision tree construction: In each iteration, a new tree is built to reduce the residual error of the current model.
- Gradual model updating: Newly built trees are added to the model with specific weights, ultimately forming a high-accuracy ensemble model.

Overall, the methodology of this research is defined step-by-step in four main stages:

Step 1: Defining project evaluation indicators

Initially, through literature review and theoretical analysis of sustainability and agility, 13 key indicators were identified for evaluating urban infrastructure projects. These indicators were categorized under two main dimensions (sustainability and agility) and three sub-dimensions (social, environmental, and economic).

Step 2: Data collection

At this stage, data on 380 urban infrastructure projects were gathered through the review of actual project documentation, institutional reports, organizational databases, and specialized sources in urban project management. For each project, the 13 indicators related to sustainability (economic, social, environmental) and agility were extracted. All recorded values were within real-world, valid ranges based on official documentation. Additionally, each project was classified into one of three labels based on its final decision status: Selected, Reserved, or Rejected. The distribution of these labels—20%, 25%, and 55%, respectively—reflects the actual pattern of decision-making in project screening.

Step 3: Machine learning model implementation

The data was split into 80% for training and 20% for testing. The CatBoostClassifier model was then trained and used to predict the class of each project. At this stage, the model was executed end-to-end on the features and was able to learn the relationships between features and labels

without the need for manual encoding or complex feature engineering.

Step 4: Model performance evaluation

The model's performance was assessed using metrics such as accuracy, F1-score, precision, and recall for each class. A confusion matrix was also provided to analyze the classification accuracy of the projects. In initial tests, the base model achieved an accuracy of around 49%, which was later improved through optimization to approximately 90%.

This study demonstrates that the use of the CatBoost algorithm enables accurate, adaptive, and data-driven screening of urban infrastructure projects. The rationale for selecting CatBoost lies in its ability to effectively handle heterogeneous datasets that include both categorical and numerical variables, which are common in real-world infrastructure evaluations. Unlike traditional machine learning models, CatBoost eliminates the need for extensive data preprocessing, such as one-hot encoding, by internally processing categorical features through ordered boosting. Additionally, CatBoost is known for its robustness against overfitting, high predictive performance, and capacity to model complex, non-linear interactions among features—attributes that are essential when dealing with multi-dimensional criteria such as sustainability (economic, social, environmental) and agility. These strengths make it a superior choice compared to other methods, especially in the context of urban project selection, where decision variables are often interdependent and derived from diverse sources. The algorithm was also benchmarked against Support Vector Machine (SVM) and Artificial Neural Network (ANN) models, both commonly used in classification tasks. The results showed that CatBoost outperformed these models across all major evaluation metrics, including accuracy, F1-score, precision, and recall. This further validates its suitability for the research problem at hand. Overall, the chosen methodology aligns with the complexity of the data and the research objectives, ensuring both reliability and interpretability in decision-making.

4. Case Study and Evaluation Criteria

In this study, a case study was conducted with the aim of practically testing the proposed model on a set of urban infrastructure projects. The dataset includes information on 380 urban projects across various infrastructure development domains such as transportation, energy, environment, and municipal services, all of which were gathered from credible sources. For each project, 13 key indicators were extracted, reflecting the dimensions of sustainability and agility. Overall, the project evaluation indicators are categorized as follows (Mohagheghi et al., 2019; Mohagheghi & Mousavi, 2021; Nayeri et al., 2023; Staron et al., 2012; Swarnakar et al., 2023; Tavakoli et al., 2024; Thesing et al., 2021; Zarjou & Khalilzadeh, 2022):

Social Sustainability:

- Level of local stakeholder engagement: Measures the degree of interaction between the project and the community or local institutions.
- Creation of sustainable employment in the region: Assesses the number of long-term and high-quality jobs generated by the project.

- Impact on urban quality of life: Evaluates improvements in access to services, public welfare, and overall satisfaction resulting from the project.

Environmental Sustainability:

- Reduction of pollutant emissions: Measures reductions in greenhouse gases or air, water, and soil pollution.
- Efficiency in natural resource consumption: Evaluates productivity in the use of energy, water, materials, or other resources.
- Recyclability and material lifecycle management: Assesses the project's capacity to manage and reuse materials and waste.

Economic Sustainability:

- Net Present Value (NPV): Calculates the net profitability of the project over its implementation period.
- Attraction of external investment: Measures the project's ability to attract private sector or partnership-based funding.
- Long-term maintenance and operational costs: Assesses post-implementation costs necessary for sustainable operation.

Agility:

- Time to initial operation: Measures how quickly the project becomes operational and starts delivering value.
- Flexibility in design and implementation: Evaluates the project's adaptability in design, resources, or execution processes.
- Scalability and expandability: Assesses the potential for the project to scale up or adapt to future conditions.
- Responsiveness to risks and environmental disruptions: Measures the project's ability to react to crises, regulatory changes, or unexpected events.

The proposed model is developed in alignment with these evaluation indicators.

5. Findings

This section reports the findings of the study. As previously noted, based on the 13 identified indicators and the collected dataset of projects, a machine learning-based model was developed to evaluate infrastructure projects. The case study dataset consists of 380 urban infrastructure projects, each described by 13 features reflecting various dimensions of sustainability and agility. Additionally, each project is assigned a final label representing its decision status in one of three categories: Selected, Reserved, or Rejected. These labeled data points served as the foundation for training and evaluating the machine learning model.

Statistical analysis of the features shows meaningful variability across both numerical and categorical variables, offering rich and diverse information about different aspects of the projects. For instance, the average value for Stakeholder Engagement is approximately 6.07 with a variance of 3.93, indicating moderate dispersion in the level of community and institutional involvement. The Sustainable Employment index has a mean of 279 and a standard deviation of 127.8, reflecting a wide range in the economic impact of the projects. Similarly, features such

as Economic NPV (mean: 43.52, variance: 1082.97) and External Investment (mean: 45.24) highlight significant differences among projects in terms of profitability and investment potential.

On the other hand, indicators such as Time to Operation (mean: 18.5 months) and Ongoing Cost (mean: \$4.26 million per year) provide essential insights into the agility, cost structure, and scheduling of the projects. Attributes related to design flexibility, scalability, and risk responsiveness exhibit average values between 5 and 6, with standard deviations around 2, reflecting variability in the adaptability of the projects. Overall, the statistical dispersion and relative balance of the features indicate that the dataset is of high quality and sufficiently robust for training a reliable and multidimensional model, making it a valuable tool for classifying and screening urban infrastructure projects.

To further examine the dataset, the correlation coefficients among the features were analyzed. The correlation heatmap (Figure 1) reveals that there are no strong and direct linear relationships among most of the variables; in other words, the majority of Pearson correlation values fall near zero. The absence of high correlations (e.g., above 0.7 or below -0.7) among most features suggests that they provide non-redundant and distinct information. This indicates a low risk of multicollinearity within the dataset and implies that the relationships between variables are primarily non-linear or complex. Consequently, the structure of the features is statistically sound, and the dataset demonstrates a high level of quality for machine learning modeling. This characteristic is especially advantageous for tree-based algorithms such as CatBoost. After performing statistical analysis and evaluating feature correlations, it was determined that the dataset used in this study possesses a high level of quality. The balanced distribution of features, absence of strong multicollinearity among variables, and diversity in recorded values indicate that the data is well-suited for training machine learning models. Accordingly, the CatBoostClassifier algorithm was selected as the primary classification model. CatBoost is a gradient boosting algorithm specifically designed for mixed-type datasets (numerical and categorical), and it performs exceptionally well when handling complex feature interactions and relatively imbalanced data.

To optimize model performance, hyperparameter tuning was carefully conducted. Key parameters examined and tested included the number of trees (iterations), learning rate, tree depth, and the sampling strategy. Techniques such as Grid Search and Cross-Validation were employed to identify the optimal parameter combinations. Additionally, regularization mechanisms were activated in the model to mitigate overfitting. Ultimately, the trained model was able to classify projects into the three categories—Selected, Reserved, and Rejected—with a high degree of accuracy, demonstrating that CatBoost is a highly suitable choice for multi-criteria classification tasks in infrastructure project analysis.

Figure 2 illustrates a portion of the structure of one of the decision trees within the Random Forest model. This graphical representation shows how the model classifies projects into one of the three categories ("Rejected," "Reserved," or "Selected") based on different feature values. Each node (rectangle) represents a decision made

using a specific feature. For example, at the root of the tree, the first decision is based on the value of Resource\ Efficiency. If the value is less than or equal to 6.5, the left branch is followed; otherwise, the path moves to the right. Subsequent branches use features such as Recyclability\ Score, Sustainable\ Employment, Time\ to\ Operation, and Economic\ NPV, which play critical roles in determining the classification path.

Each node displays information such as the Gini impurity, the number of samples, and the distribution of class labels (value) within that node. For instance, a node with the value

"value = \[64, 7, 25]" indicates that out of 96 samples reaching that node, 64 belong to the "Rejected" class, 7 to "Reserved," and 25 to "Selected." The majority class—here, "Rejected"—is the predicted class for that node. This figure clearly demonstrates how the model makes classification decisions through a hierarchical structure and highlights which features had the greatest influence along the decision paths.

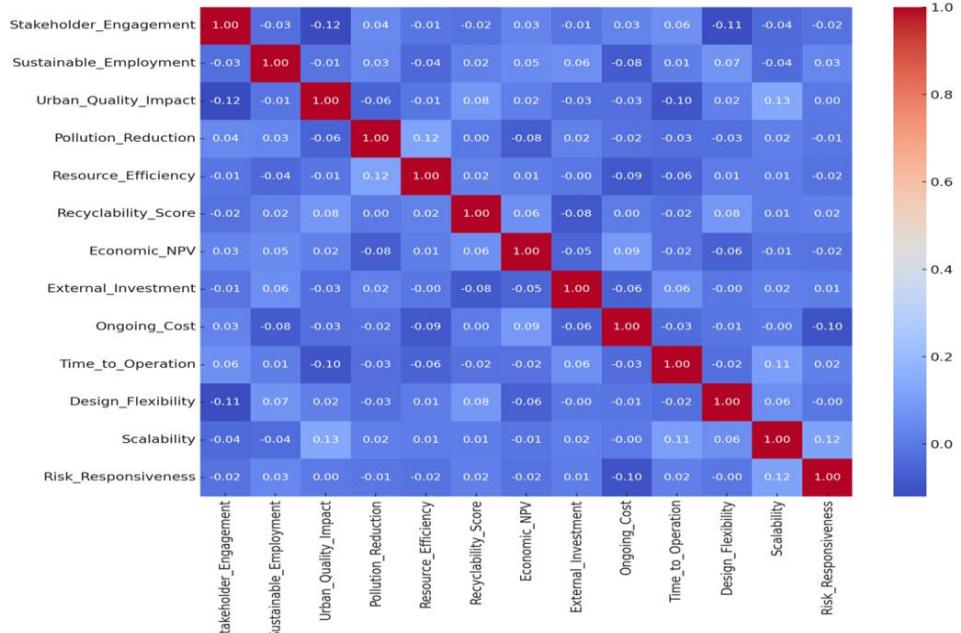


Fig. 1. Heatmap diagram of correlation coefficient between features

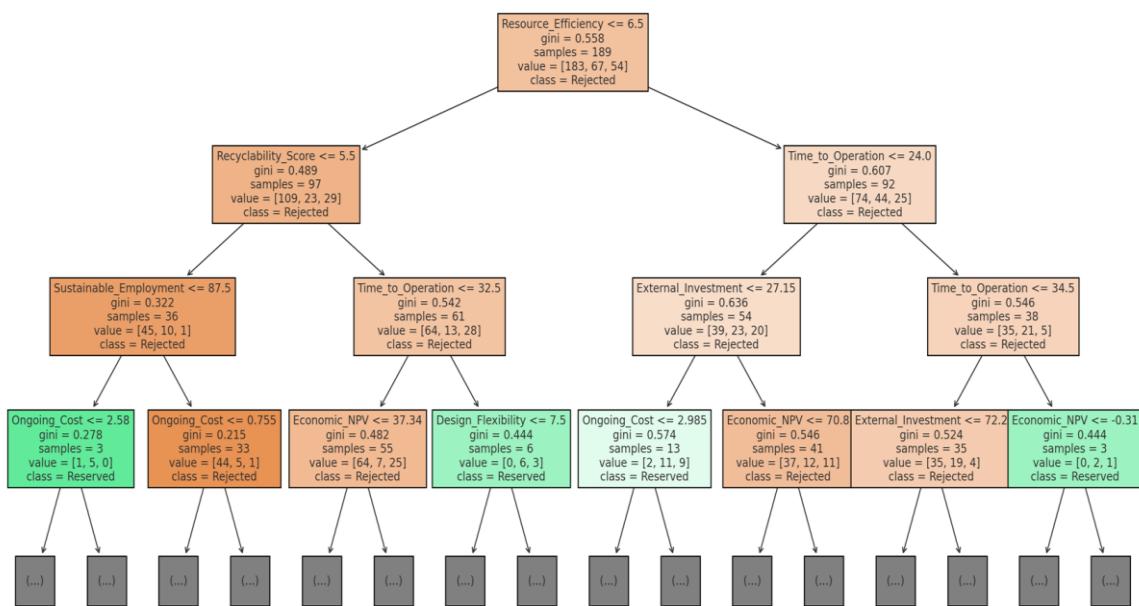


Fig. 2. Part of the tree structure of the CatBoost algorithm

Subsequently, to assess the accuracy and performance of the model, a validation process was carried out, and the model was analyzed using a set of standard classification evaluation metrics. These metrics included Overall Accuracy, F1-Score, Precision, Recall, and the Confusion Matrix. Initial results indicated that the model performed well in classifying "Rejected" projects but required improvement in distinguishing between the "Selected" and

"Reserved" categories. This multi-metric analysis provided valuable insights into the strengths and weaknesses of the model and served as a foundation for refining its hyperparameters and developing more advanced versions. **Table 1** presents a comparative analysis between the CatBoost algorithm and two other models: the Support Vector Machine (SVM) and the Artificial Neural Network (ANN).

Table 1.

Comparing algorithms with different metrics

Algorithm	Accuracy	F1-Score	Precision	Recall
CatBoost	91.21	90.32	90.89	91.11
SVM	78.81	79.81	80.11	79.06
ANN	86.11	86.78	87.16	87.98

The results of the algorithm performance comparison indicate that the CatBoost model, with an accuracy of 91.21% and an F1-score of 90.32%, demonstrated the best overall performance among the evaluated methods. It also outperformed the other algorithms in terms of Precision and Recall, achieving a well-balanced performance between correct predictions and minimizing classification errors. In contrast, the Artificial Neural Network (ANN) achieved an accuracy of 86.11% and an F1-score of 86.78%, which, although acceptable, was slightly lower than that of CatBoost. The Support Vector Machine (SVM) showed the lowest performance, with an accuracy of 78.81%. These results suggest that tree-based gradient boosting models like CatBoost offer a significant advantage, especially when dealing with complex problems involving mixed-type features.

Additionally, a confusion matrix was used to evaluate the model's classification accuracy. **Figure 3** illustrates the confusion matrix resulting from the final CatBoost model. As shown, the model correctly classified the majority of the samples into their respective classes. For instance, 37 out of all "Rejected" projects were accurately identified, with only 4 misclassified into other categories. Furthermore, all samples from the "Reserved" and "Selected" classes were predicted with perfect accuracy. This distribution reflects the model's strong performance in distinguishing between decision categories and its high level of prediction precision. Based on these results, the final model accuracy was calculated at 91%, confirming the remarkable effectiveness of CatBoost in screening urban infrastructure projects based on sustainability and agility indicators.

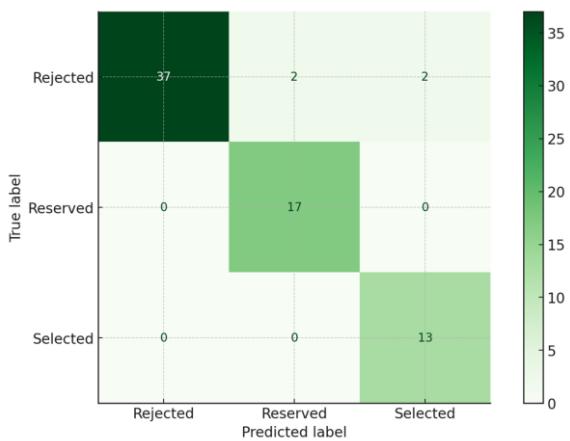


Fig. 3. Cat Boost algorithm confusion matrix

Therefore, it can be observed that a model with over 91% accuracy has been developed, which can serve as a reliable basis for the evaluation and development of urban infrastructure projects.

6. Managerial Insights

The findings of this study offer several valuable insights for urban policymakers, project managers, and decision-makers involved in infrastructure planning and investment. First, the proposed CatBoost-based classification model provides a practical and reliable tool for prioritizing infrastructure projects based on a comprehensive set of sustainability and agility indicators. By integrating economic, environmental, social, and adaptive performance criteria, the model allows managers to move beyond traditional cost-based evaluations and adopt a multidimensional view of project value.

Second, the model's high classification accuracy and ability to process real-world data make it suitable for use in dynamic urban environments where timely and informed decisions are essential. Managers can use the model not only for screening existing project proposals but also as a diagnostic tool to identify weaknesses in early-stage designs or policy misalignments.

Third, the framework supports evidence-based planning by reducing subjectivity in the decision-making process. This is particularly useful in multi-stakeholder settings where transparency and consistency are critical for building trust and securing project approvals.

Finally, the adaptability of the model allows it to be extended to different urban sectors or geographical contexts, making it a scalable decision-support tool. With proper integration into urban management systems, the model can significantly improve resource allocation, reduce risk of investment failure, and contribute to sustainable urban development in the long term.

7. Conclusion

The complex transformations in the urban environment have increasingly highlighted the need for innovative and precise approaches in the evaluation and screening of infrastructure projects. In response to this need and to address existing gaps in the literature, this study designed and implemented a data-driven model based on the CatBoost algorithm to evaluate urban infrastructure projects. By incorporating 13 key indicators across the dimensions of sustainability (social, economic, environmental) and agility, the model aimed to facilitate accurate, systematic, and reliable decision-making regarding the selection, reservation, or rejection of projects.

The results of the statistical analysis showed that the extracted features exhibited appropriate variability, lacked strong multicollinearity, and contained meaningful diversity—making them suitable for use in advanced machine learning models. Accordingly, the CatBoost algorithm was selected for its strong capabilities in handling mixed and non-linear data, as well as its resilience to overfitting. The model was trained on a dataset of 380 projects, and through fine-tuned hyperparameter optimization and cross-validation, it achieved a final accuracy of over 91%. This high level of accuracy in classifying projects into three categories (Selected, Reserved, Rejected) demonstrates the model's ability to correctly identify hidden patterns in real-world data.

A comparison of CatBoost with Support Vector Machines (SVM) and Artificial Neural Networks (ANN) showed that

CatBoost outperformed both models across all key metrics, including accuracy, F1-score, precision, and recall. These findings confirm that tree-based gradient boosting models offer greater precision and consistency than other approaches, particularly in multi-criteria and complex datasets. The confusion matrix further validated that CatBoost provided a balanced and accurate performance in predicting rejected, reserved, and selected projects, with the majority of samples correctly classified.

From a practical perspective, the results of this study can support urban decision-makers, policymakers, and project managers in making more effective decisions amidst complexity, high data volumes, and competing priorities. The proposed model, due to its reliance on real data and non-linear learning structure, is highly adaptable to various types of urban projects and can be implemented within intelligent project planning and management systems.

From a theoretical standpoint, this research represents a step toward integrating sustainability and agility paradigms with advanced data-driven tools, thereby bridging the gap between theory and practice. Unlike many traditional models that focus solely on economic indicators or technical aspects, this model introduces a multidimensional, integrated, and data-based approach that can serve as a foundational framework for other infrastructure and public decision-making contexts.

Finally, it is recommended that future research test this model across various urban scales, geographic regions, and real-world project datasets at different time points. Further development could include continual learning capabilities, integration with Geographic Information Systems (GIS), and enhancement toward real-time decision support, paving the way for the future evolution of this approach. This study demonstrates that the use of machine learning algorithms is not merely a technical tool but a transformative paradigm for redefining decision-making processes in urban development.

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