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Explainable machine learning for predicting the success of IT projects in Nigerien SMEs: an empirical study based on 488 projects in Niamey

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Abstract. IT projects play a crucial role in the digital transformation of small and medium-sized enterprises (SMEs), but their success remains highly dependent on organizational, financial, and infrastructural constraints, particularly in developing countries. This study proposes an explainable predictive framework for the success of IT projects applied to SMEs in Niamey, Niger's main digital hub. The analysis is based on a set of 488 IT projects and compares the performance of seven machine learning algorithms: logistic regression, decision tree analysis, random forest analysis, support vector machines (SVMs), k-nearest neighbors, gradient boosting, and XGBoost. A rigorous methodology integrating data preprocessing, hyperparameter optimization using GridSearchCV, and cross-project validation based on GroupKFold was implemented. The results show that the SVM model achieved the highest predictive performance with an AUC-ROC of 0.850. To improve the interpretability of the predictions, explainable artificial intelligence analyses based on SHAP were conducted. These analyses revealed that stakeholder satisfaction, budget overruns, delays, project complexity, and certain constraints related to power supply and internet availability are the main determinants of project success. The study also led to the development of a prototype early warning system designed to support decision-making and proactively manage IT projects in SMEs.

Keywords: Explainable Machine Learning; IT Projects; Small and Medium Enterprises; Success Prediction; Early Warning System.

1. Introduction

Digital transformation has become a key driver of competitiveness, innovation, and resilience for small and medium-sized enterprises (SMEs). The increasing adoption of digital technologies, the dematerialization of services, and the development of entrepreneurial ecosystems are fostering the emergence of new economic opportunities, particularly in developing countries (Bangarigadu & Nunkoo, 2023).

In Africa, this dynamic has intensified in recent years due to the gradual spread of digital infrastructure and the rise of technology startups (Nishat et al., 2025). In this context, IT projects occupy a strategic position in the processes of business modernization and the transformation of organizational models (Schwalbe, 2021). Despite their growing importance, IT projects continue to experience high failure rates worldwide.

Cost overruns, delays, poor risk management, and weak organizational coordination remain major factors in the failure of digital projects (Schwalbe, 2021). This problem is even more pronounced in environments characterized by significant structural and infrastructural constraints. In several African countries, SMEs operate in contexts marked by unstable internet connectivity, frequent power outages, limited financial resources, and the low maturity of digital governance mechanisms (Bangarigadu & Nunkoo, 2023; Razaghzadeh B. M. et al., 2024). These constraints reduce the likelihood of project success and complicate their management. Traditionally, project management relies on descriptive approaches and static indicators, primarily used to evaluate performance after the fact. While these methods remain useful, they have significant limitations when it comes to anticipating problems before they lead to project failure (Santos et al., 2023).

In complex and rapidly evolving environments, conventional approaches thus show shortcomings in terms of prediction, proactive risk management, and decision support. Faced with these limitations, machine learning techniques are attracting increasing interest in the field of project management. Thanks to their ability to learn from historical data, these methods make it possible to identify complex relationships between organizational, technical, and environmental factors that can influence project performance (Hastie et al., 2021). Several recent studies have demonstrated the effectiveness of supervised approaches in predicting the risks and success of digital projects (Berriche et al., 2025; Nishat et al., 2025). In particular, ensemble methods such as Random Forest, Gradient Boosting or XGBoost generally offer superior performance to traditional linear models in complex classification problems (Goodfellow et al., 2016).

However, improved predictive performance is often accompanied by increased model complexity. Many high-performing algorithms function as "black boxes," making it difficult to understand the mechanisms that led to a given decision. This opacity limits user trust and is a significant obstacle to the adoption of artificial intelligence systems in decision-making environments (Haldar & Capretz, 2023). In this context, Explainable Artificial Intelligence (XAI) has emerged as a major research area. Explainability approaches aim to make models more transparent and interpretable, thereby improving their organizational acceptability (Saarela & Podgorelec, 2024). Among the most popular techniques, SHAP (SHapley Additive exPlanations) allows for the quantitative explanation of the influence of variables on the predictions produced by machine learning models (Lundberg & Lee, 2017; Salih et al., 2025).

Despite the progress observed in this field, several limitations remain in the current literature. First, the majority of studies on predicting the success of IT projects have been conducted in Western contexts or using international industrial databases, leaving relatively little room for African environments. Second, studies simultaneously combining machine learning, explainable artificial intelligence, temporal structuring of data, and robust validation remain scarce. Finally, few studies go so far as to transform predictive results into operational decision-making tools accessible to managers.

This research aims to contribute to reducing these gaps by proposing an explainable analytical framework applied to the IT projects of Nigerien SMEs. The study focuses exclusively on the city of Niamey, Niger's main digital hub. This choice is justified by the fact that the majority of the country's IT SMEs, technology startups, and digital transformation initiatives are concentrated there. This high concentration of digital activities provides a relatively homogeneous environment in economic, organizational, and technological terms, thus reducing structural heterogeneity between regions. The analysis is based on a set of 488 IT projects identified in the Niamey region, offering a coherent empirical basis for studying the determinants of success for digital projects.

Beyond its scientific and methodological contributions, this research aligns with the United Nations Sustainable Development Goals. By contributing to improved management and success rates of digital projects within SMEs, it directly contributes to achieving Sustainable Development Goal 9, which focuses on industry, innovation, and resilient infrastructure. Furthermore, strengthening the performance of IT projects and the resilience of SMEs indirectly contributes to Sustainable Development Goal 8, dedicated to promoting sustainable economic growth and decent work.

The main objective of this research is to develop an explainable predictive model capable of anticipating the success or failure of IT projects in Niamey SMEs by combining machine learning, temporal data structuring, and explainable artificial intelligence. More specifically, the study aims to compare several machine learning algorithms, integrate panel modeling to track the dynamic evolution of projects, improve methodological robustness through inter-project validation based on GroupKFold, interpret predictions using the SHAP method, and develop an operational prototype for decision support in the form of an intelligent dashboard.

Four main hypotheses are formulated:

1. H1: ensemble models outperform classical approaches in predicting the success of IT projects;
2. H2: integrating temporal variables significantly improves predictive performance;
3. H3: the exPlainability of models strengthens their decision-making relevance and organizational acceptability;

4. H4: infrastructural constraints strongly influence the success of IT projects in SMEs in Niamey.

The main contributions of this research lie in the application of explainable Machine Learning to a still little studied context, the joint integration of SHAP, GroupKFold validation and a temporal panel structuring, the development of an intelligent early warning system for the management of IT projects as well as the proposal of a reproducible methodological framework and potentially transferable to other African environments.

2. Literature Review and Conceptual Framework

2.1. Success and Failure of IT Projects

The success of IT projects has been a central issue in project management, information systems, and digital transformation for several decades. Despite advances in management methodologies, digital technologies, and collaborative tools, IT projects continue to experience relatively high failure rates. According to Schwalbe (2021), many projects still face budget overruns, delivery delays, frequent changes in requirements, and coordination difficulties among stakeholders. These challenges are particularly pronounced in environments characterized by limited resources and significant organizational instability.

Traditionally, project success was assessed by adhering to the cost-time-quality triad. However, this approach is now insufficient to reflect the increasing complexity of digital projects. Several recent studies show that the success of a project also depends on user satisfaction, value creation, the quality of governance, risk management, and the ability to adapt to change (Kerzner, 2022; Bangarigadu & Nunkoo, 2023; Razaghzadeh B.M. et al., 2024). In the context of SMEs, the availability of human resources, organizational capabilities, and the technological environment are also determining factors (Nazeer & Marnewick, 2022).

The governance of digital projects thus plays a crucial role in organizational performance. According to Santos et al. (2023), the implementation of effective planning, coordination, and monitoring mechanisms contributes significantly to risk reduction and improved project performance. Similarly, Denyer (2022) emphasizes that organizations capable of developing resilience mechanisms are better prepared to cope with disruptions and maintain business continuity.

The emergence of digital transformation has also reinforced the importance of contextual factors. In developing countries, IT projects operate in environments marked by economic, organizational, and infrastructural constraints that can affect their performance (World Bank, 2022).

In the African context, several authors emphasize that traditional project management models do not always allow for consideration of local specificities related to infrastructure availability, energy constraints, and the digital maturity of businesses (Bangarigadu & Nunkoo, 2023; Nishat et al., 2025). These observations highlight the need to develop approaches better suited to resource-constrained environments, capable of simultaneously integrating the technical, organizational, and contextual dimensions that influence the success of IT projects.

2.2. Machine Learning Applied to Project Management

The emergence of Machine Learning (ML) has profoundly transformed traditional project management approaches by introducing predictive analytics mechanisms capable of leveraging historical data to anticipate risks and improve decision-making. Unlike classical statistical methods, supervised learning techniques make it possible to identify complex relationships between multiple variables and extract patterns that are difficult to observe using conventional approaches (Hastie et al., 2021). These advances pave the way for intelligent systems capable of improving project monitoring, optimizing resource allocation, and reducing the probability of failure.

Among the most commonly used methods, logistic regression is a benchmark approach for binary classification problems. Its main advantage lies in its simplicity and interpretability, making it a frequently used basic model in comparative studies (James et al., 2021). However, its performance can be limited when the interactions between variables become highly nonlinear.

Decision trees are also widely used tools due to their intuitive nature and ease of interpretation. They allow for the generation of explicit decision rules, but their susceptibility to overfitting can reduce their generalizability (Pedregosa et al., 2011). To overcome these limitations, ensemble methods have seen considerable development in recent years. Introduced by Breiman (2001), the Random Forest method relies on aggregating a set of decision trees to improve the robustness of predictions and reduce model variance.

Several recent studies show that this approach offers high performance in complex risk classification and prediction problems (Berriche et al., 2025). Similarly, boosting methods, such as Gradient Boosting and XGBoost, progressively improve performance by correcting errors made during previous iterations. XGBoost, proposed by Chen and Guestrin (2016), is now considered one of the most efficient algorithms in many areas of predictive analytics.

Support Vector Machines (SVMs), introduced by Cortes and Vapnik (1995), are also widely used in high-dimensional classification problems. Thanks to their ability to construct optimal separation boundaries, they provide robust performance in environments characterized by complex relationships between variables. The work of Haldar and Capretz (2023) has shown that SVMs yield particularly interesting results in problems related to software defect prediction and project metric analysis.

K-Nearest Neighbors (KNN) methods, based on the proximity of observations, offer a simple and effective alternative in certain contexts. However, their sensitivity to data dimensionality can limit their performance when the number of variables becomes large (James et al., 2021).

The applications of machine learning to project management have multiplied in recent years. Bangarigadu and Nunkoo (2023) showed that supervised approaches can effectively predict the performance of small businesses and identify factors associated with organizational success. Similarly, Razaghzadeh B. M. et al. (2024) demonstrated the relevance of ensemble models for predicting the success of startups and innovative projects. The work of Santos et al. (2023) highlights the value of machine learning in developing decision support systems for project management.

More recently, Nishat et al. (2025) showed that machine learning techniques are particularly promising tools for predictive project analysis and the early detection of deviations. Along the same lines, highlighted the value of machine learning for anticipating variations and changes in complex projects, while Berriche et al. (2025) showed that hyperparameter optimization and ensemble approaches significantly improve the accuracy of failure prediction models.

Despite their performance, traditional machine learning approaches still have several limitations. Firstly, most models operate as "black box" systems, which reduces their acceptability in decision-making environments. Secondly, classical approaches rarely consider temporal dependencies and relationships between observations belonging to the same set of data.

2.3. Explainable AI and SHAP

The continuous improvement in the performance of machine learning models has been accompanied by an increase in their complexity, leading to the emergence of models often described as "black boxes." While these models offer high predictive capabilities, their lack of transparency is a major obstacle to their adoption in decision-making environments where trust, traceability, and accountability are essential (Adadi & Berrada, 2018). This issue is particularly important in project management, where decision-makers need to understand the factors behind predictions in order to implement appropriate corrective actions.

To address these limitations, the field of Explainable Artificial Intelligence (XAI) has experienced considerable growth in recent years. According to Molnar (2022), the fundamental goal of XAI is to make artificial intelligence systems more interpretable and understandable for human users. More recently, Saarela and Podgorelec (2024) show that interest in explainable methods is growing rapidly in many application areas, including healthcare, finance, industry, and decision support systems.

Explicability approaches can be classified into intrinsic and post-hoc methods. The former rely on naturally interpretable models, while the latter explain decisions produced by already trained, complex models (Molnar, 2022). Among these approaches, LIME and SHAP methods currently appear to be the most widely used in recent literature (Salih et al., 2025).

Introduced by Lundberg and Lee (2017), SHAP (SHapley Additive exPlanations) uses cooperative game theory and Shapley values to assign each variable a quantitative contribution to the final prediction. This approach possesses several important theoretical properties, including consistency, symmetry, and additivity, which enhance the reliability of the explanations produced. Recent work confirms that SHAP is now one of the most robust and widely adopted explainability methods in machine learning applications (Saarela & Podgorelec, 2024; Vimbi et al., 2024).

One of the main advantages of SHAP lies in its ability to simultaneously provide global and local interpretations. Global analyses help identify the most influential variables in the model's behavior, while local explanations facilitate understanding of individual predictions (Lundberg & Lee, 2017). Graphical representations associated with SHAP values, such as Summary Plots, Dependence Plots, and Waterfall Plots, contribute to improving the readability and interpretation of the results (Cunha & Barbosa, 2024).

Several recent studies show that explainable artificial intelligence methods significantly improve the transparency, trust, and acceptability of decision support systems (Haldar & Capretz, 2023; Santos et al., 2023). The work of Givisis et al. (2025) also highlights that SHAP exhibits superior discriminatory capabilities compared to several other explainability methods in certain complex applications.

In the field of project management, the integration of XAI not only enables reliable predictions but also the identification of critical factors responsible for delays, budget overruns, or risks of failure. This explanatory dimension appears particularly important in SMEs, where managers often have limited resources and need simple, transparent, and understandable tools to support their strategic decisions. Thus, the combination of machine learning and explainable artificial intelligence represents a promising avenue for transforming predictive models into truly intelligent decision support systems.

2.4. Longitudinal Approaches and Robust Validation

The quality of performance achieved by machine learning models depends heavily on the validation strategy adopted. In project management applications, observations are often characterized by temporal dependencies and correlations between data points belonging to the same project. In this context, traditional approaches based on random data splitting can introduce information leakage that may lead to an overestimation of model performance (Kuhn & Johnson, 2019).

Longitudinal data, also known as panel data, allows for tracking the evolution of a phenomenon over time by combining temporal and individual dimensions. This structure is particularly well-suited to IT projects, whose performance evolves gradually based on accumulated delays, budget overruns, and changes in specifications (Hsiao, 2022). Panel data thus offers a better representation of the actual dynamics of projects and allows for the integration of trend and instability indicators into predictive models.

Several recent studies highlight the importance of adopting more rigorous validation procedures to ensure the generalizability of models (Nishat et al., 2025; Berriche et al., 2025). Stratified cross-validation remains widely used to preserve class distribution, but it does not always prevent dependencies between observations belonging to the same group (Pedregosa et al., 2011).

To mitigate this risk, approaches based on GroupKFold enable partitioning while ensuring that the same group never appears simultaneously in the training and test sets. This strategy helps limit information leakage and provides a more realistic estimate of model performance (Pedregosa et al., 2011; James et al., 2021). Furthermore, temporal validation approaches are increasingly recommended in predictive systems to respect data chronology and improve model robustness in dynamic environments (Molnar, 2022).

Thus, combining longitudinal data, temporal validation, and inter-group validation mechanisms represents a promising methodological approach for strengthening the reliability and generalizability of machine learning-based decision support systems.

2.5. Identified Scientific Gap

Despite significant progress in applying machine learning to project management, several gaps remain in the current literature. First, most recent work has been conducted in Western contexts or using international databases, with limited representation of African environments and SMEs operating under resource constraints (Bangarigadu & Nunkoo, 2023; Nishat et al., 2025). This situation limits the ability of existing models to account for the specific economic, organizational, and infrastructural characteristics of developing countries.

Second, studies that jointly integrate explainable artificial intelligence and project success prediction remain scarce. Although Santos et al. (2023) and Haldar and Capretz (2023) have demonstrated the value of SHAP in improving model interpretation, applications to the IT project domain remain limited.

Finally, few studies combine longitudinal data, cross-project validation, and operational decision support systems. According to Saarela and Podgorelec (2024), the development of explainable and robust predictive models remains a major challenge for artificial intelligence-based decision-making systems. In this context, the present study aims to address these gaps by proposing a framework integrating machine learning, SHAP, panel structuring, and GroupKFold validation, applied to the 488 IT projects identified in the city of Niamey.

3. Methodology

3.1. Study Area: Niamey

This study focuses exclusively on the city of Niamey, the political, administrative, and economic capital of Niger. This choice is motivated by the fact that the majority of the country's IT SMEs, technology startups, digital incubators, and digital transformation initiatives are concentrated there.

The projects carried out in Niamey reflect the main constraints encountered in African digital environments, including:

- Budgetary limitations;
- Energy instability;
- Connectivity difficulties;
- Challenges related to digital governance.

This geographic concentration helps reduce structural heterogeneity between regions and improve the analytical consistency of the dataset.

The final sample comprises 488 IT projects identified in the Niamey region. The data used in this study comes from an empirical survey conducted between august 2025 and february 2026 among IT SMEs in Niamey, Niger. The data collection protocol included:

- Identifying SMEs with at least three years of operation;
- Obtaining informed consent;
- Conducting semi-structured interviews;
- Administering a structured questionnaire to project managers (Appendix 1).

The sample consisted of professionals with at least three years of experience in IT project management.

3.2. Dataset Description

The dataset gathers information on IT projects developed within SMEs in Niamey. The variables studied cover several dimensions. Organizational variables include:

- Project budget;
- Its duration;
- Team size;
- Complexity;
- Delays;
- Satisfaction level;
- Progress rate.

Infrastructural variables include:

- Internet availability;
- Frequency of power outages;

- Stability of digital resources.
- Temporal variables were also constructed:
- Cumulative delays;
- Cumulative budget;
- Delay trends;
- Progress rate;
- Project instability.

The target variable corresponds to the final project status:
- 1: success;
- 0: failure or high risk.

3.3. Data Preprocessing

Preprocessing is an essential step to improve data quality and consistency before training. Duplicates and inconsistencies were removed. Missing values were addressed by:
- Median imputation for numerical variables;
- Dominant category imputation for categorical variables.

Qualitative variables were transformed using OneHotEncoder. Numerical variables were standardized using StandardScaler to minimize the effects of scaling differences. All processing was automated via a Scikit-learn pipeline that includes:
- Imputation;
- Encoding;
- Normalization;
- Model training.

This automation improves the reproducibility of experiments and reduces the risk of data leakage.

3.4. Heuristic Baseline

Before implementing the machine learning models, a heuristic baseline was established to provide a comparative reference. This approach is based on classic rules inspired by project management practices. A project is considered at risk when at least two of the following conditions are met:
- Delays exceeding 20%;
- Budget overruns exceeding 15%;
- Completion rate below 50%;
- High level of instability.

This approach allows us to measure the actual benefit provided by artificial intelligence models.

3.5. Machine Learning Models

Seven supervised models were compared:

- Logistic Regression;
- Decision Tree;
- Random Forest;
- Support Vector Machine;
- K-Nearest Neighbors;
- Gradient Boosting;
- XGBoost.

Ensemble models were favored because of their ability to capture complex relationships between variables and improve classification performance. Hyperparameters were optimized using GridSearchCV to improve model robustness and limit overfitting.

3.6. Temporal Panel Structure

To overcome the limitations of static approaches, the data were restructured into a panel based on a Project × Time logic. Each project is observed at several stages of its lifecycle. This structure allows for the integration of:

- Cumulative delays;
- Cumulative budgets;
- Trends;
- Progress rate;
- Levels of instability.

This representation improves the modeling of internal project dynamics and aligns the proposed approach more closely with early warning systems.

3.7. Robust Scientific Validation

Several levels of validation were implemented. A Train/Test separation allows for the evaluation of performance on unobserved data. Stratified cross-validation ensures the preservation of the class distribution. Additional internal validation based on multiple dataset partitions allows for the evaluation of performance stability.

Finally, inter-project validation using GroupKFold is introduced. This strategy ensures that no observations belonging to the same project appear simultaneously in the training and test sets. This approach improves:

- Methodological robustness;
- Generalizability;
- The scientific credibility of the results.

3.8. Explainable AI

The interpretability of the models is ensured through the SHAP method. Three levels of analysis are performed:

- SHAP Summary Plot;
- SHAP Feature Importance;

- Local interpretation.

These analyses make it possible to identify the most influential factors in the predictions and to individually explain each decision of the model. This approach improves:

- Transparency;
- Trust;
- Organizational acceptability.

3.9. Prototype Development

To transform the scientific results into an operational tool, an intelligent dashboard was developed using Streamlit. The prototype enables:

- Visualization of indicators;
- Temporal monitoring;
- Calculation of risk probabilities;
- Identification of critical projects;
- Interactive SHAP interpretation.

It thus constitutes an intelligent decision support system.

3.10. Open Science and Reproducibility

In line with open science principles, the entire experimental pipeline has been documented and published on a dedicated GitHub platform. The repository includes:

- Preprocessing scripts;
- Notebooks;
- Trained models;
- Scikit-learn pipelines;
- The Streamlit dashboard;
- Software dependencies;
- Technical documentation.

This approach aims to:

- Promote reproducibility;
- Improve scientific transparency;
- Encourage collaborations;
- Facilitate the reuse of the methodological framework.

3.11. Ethical Considerations and Responsible AI

This study adheres to the principles of responsible AI. The use of SHAP improves transparency and reduces the effects associated with black-box models. GroupKFold validation limits certain biases induced by intra-project dependencies and improves the reliability of the performance obtained.

The data was processed in accordance with the principles of confidentiality and protection of organizational information.

The proposed system is not intended to replace human decision-makers. It is a decision support tool in which human expertise retains a central role ("Human-in-the-Loop"). Finally, publishing the source code on GitHub improves:

- Auditability of the models;
- Independent verification of the results;
- Methodological transparency;
- Reproducibility of the experiments.

This combination of Machine Learning, panel data, SHAP, GroupKFold, operational dashboard, open science and responsible AI constitutes one of the main methodological originalities of this research and helps to bring predictive models closer to the real needs of digital project managers.

4. Results

4.1. Comparison of Machine Learning Models

Table 1 below provides a comparison of the metrics obtained from the seven classification algorithms evaluated as well as the results of the heuristic baseline.

Table 1. Comparison of Metrics

Model	Accuracy	Precision	Recall	F1-score	AUC-ROC
SVM	0.806	0.873	0.861	0.867	0.85
Random Forest	0.816	0.846	0.917	0.88	0.826
XGBoost	0.755	0.887	0.764	0.821	0.825
Logistic Regression	0.816	0.846	0.917	0.88	0.823
Gradient Boosting	0.724	0.869	0.736	0.797	0.789
KNN	0.673	0.833	0.694	0.758	0.778
Decision Tree	0.745	0.862	0.778	0.818	0.704
Heuristic Baseline	0.664	0.625	0.639	0.632	0.617

Among them, the Support Vector Machine (SVM) achieves the best performance with an AUC-ROC of 0.850, ahead of Random Forest (0.826), XGBoost (0.825), and logistic regression (0.823).

The decision tree exhibits the weakest performance with an AUC of 0.704. These results indicate that more sophisticated learning methods are better able to capture the complex relationships between variables describing IT projects. The similarity in performance obtained by logistic regression, Random Forest, and XGBoost also reflects a certain robustness in the prediction process.

Figure 1 shows the comparative ROC curves, which demonstrate that the models exhibit varying discrimination capabilities.

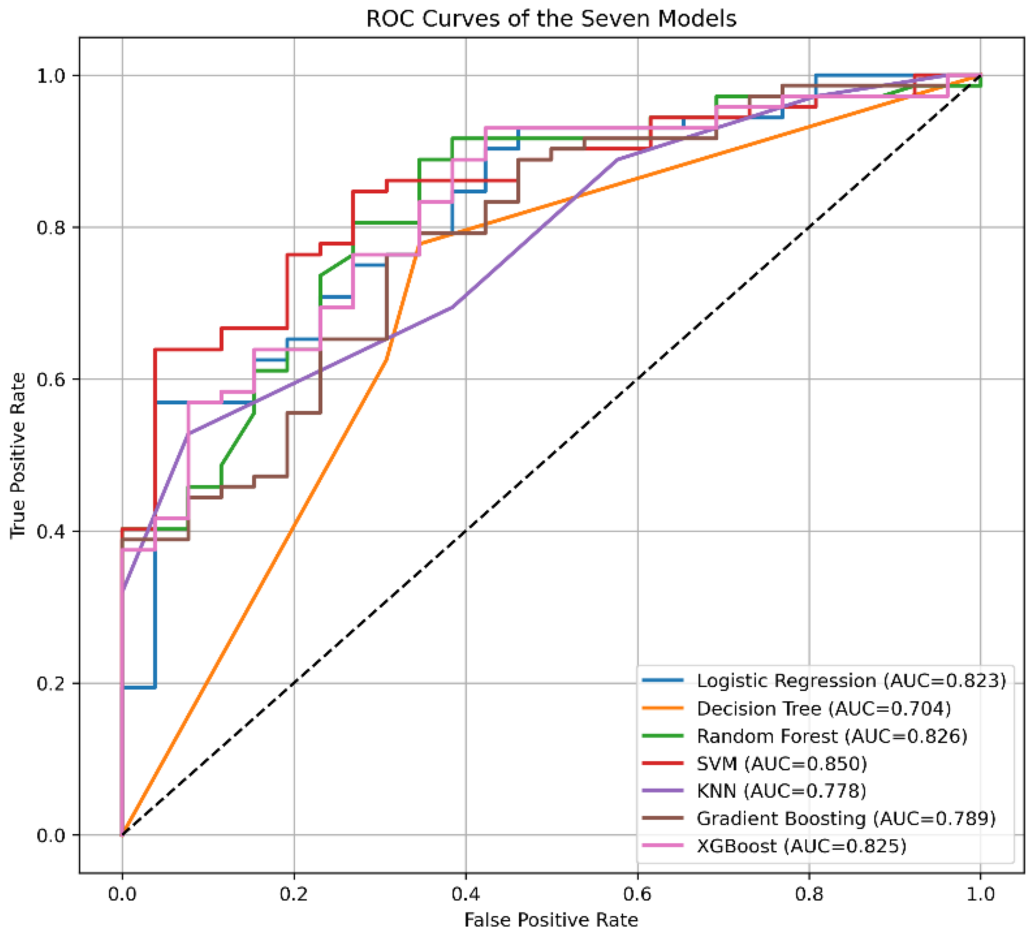

Figure 1. ROC curves of the 7 models

Figure 2 below presents the confusion matrices of the models Logistic Regression and Decision Tree.

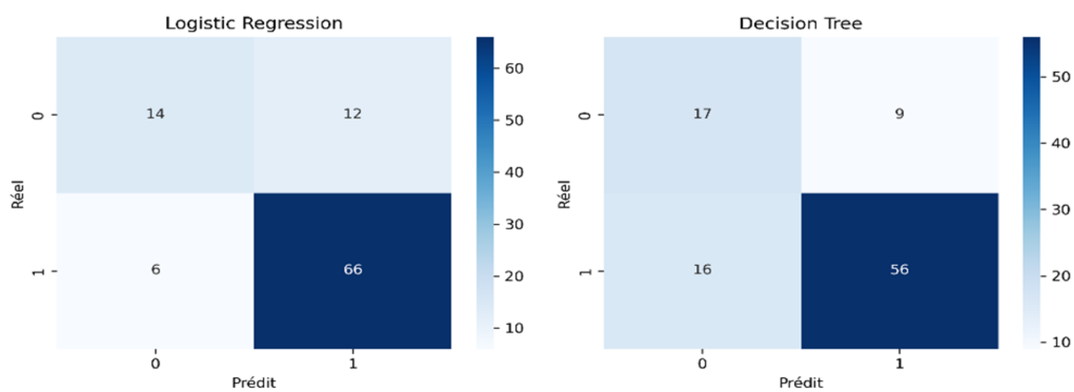

Figure 2. Confusion matrices of the models Logistic Regression and Decision Tree.

Figure 3 below presents the confusion matrices of the models SVM, KNM, XGBoost, Random Forest and Gradient Boosting.

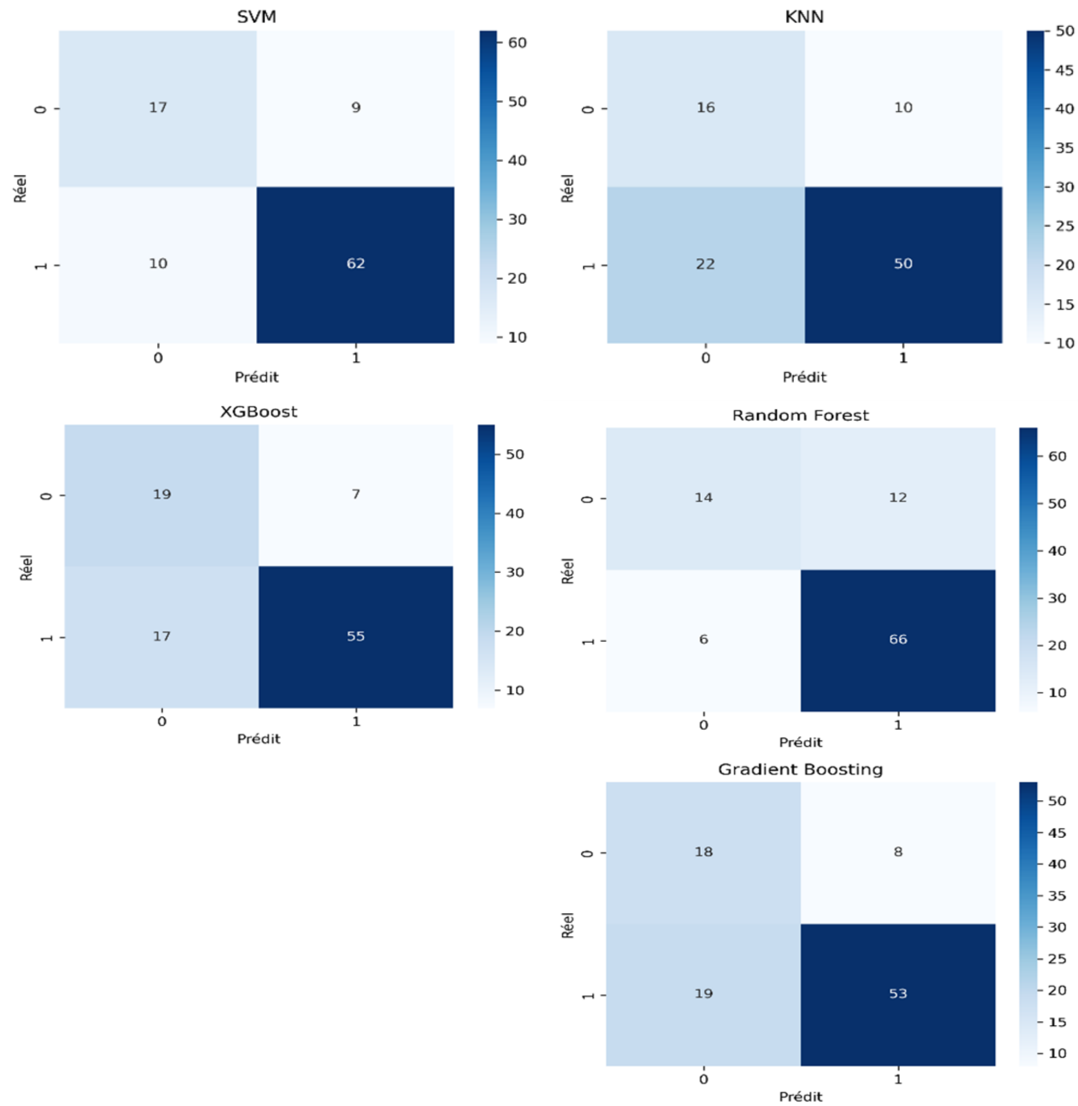

Figure 3. Confusion matrices of the models SVM, KNM, XGBoost, Random Forest and Gradient Boosting.

4.2. Analysis of the Best Model's Classification

The SVM confusion matrix shown in Figure 4 demonstrates a good project classification capability. In the test sample, 62 successful projects were correctly identified, while 17 failing projects were correctly detected. Classification errors remain relatively limited, with nine false positives and ten false negatives, confirming the model's ability to distinguish projects likely to succeed from those at risk of failure.

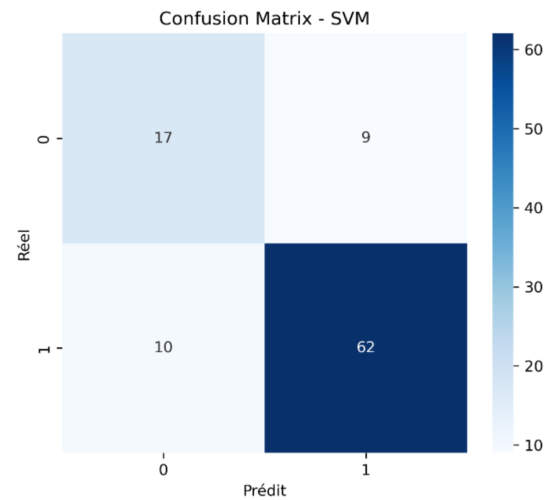

Figure 4. Confusion matrix of the best model (SVM)

4.3. Importance of explanatory variables

Figure 5 relating to the permutation analysis highlights several determining factors in predicting project success.

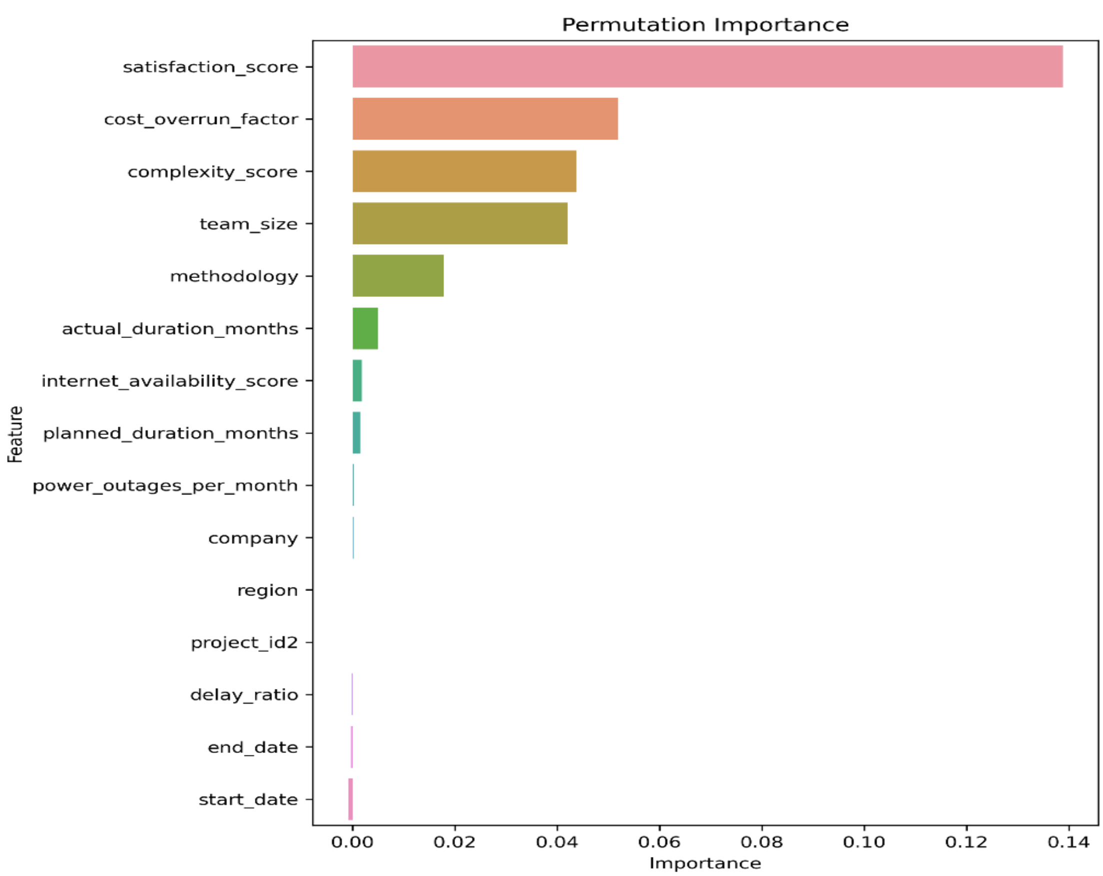

Figure 5. Permutation analysis

Stakeholder satisfaction appears to be the most influential variable, followed by budget overrun, project complexity, and team size. Development methodology, actual project duration, and internet availability also have a significant impact. Conversely, variables such as region and project dates have a marginal impact on predictive performance.

4.4. Explainable Analysis of Predictions Using SHAP

The results obtained using SHAP confirm the previous observations. The overall importance graphs (Figure 6) show that the satisfaction score is the primary determinant of IT project success, followed by budget overrun, accumulated delays, planned project duration, team size, and complexity.

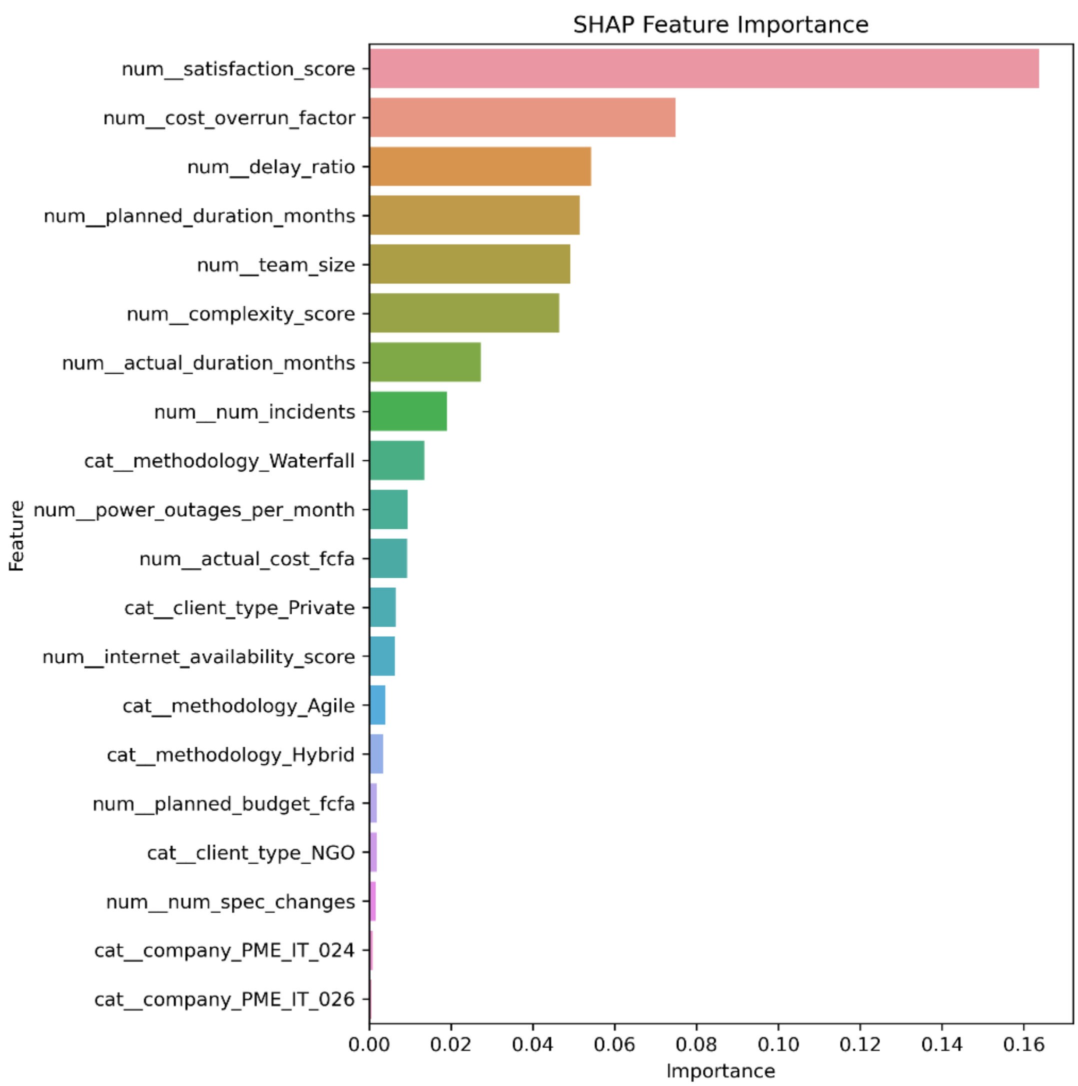

Figure 6. SHAP global explanation

Infrastructural constraints, particularly power outages and internet availability, also influence the model's decision-making process, although their contribution is more moderate. Development methods and customer type have a weaker effect on the predictions.

The SHAP dependency plot highlights a virtually monotonic relationship between the level of satisfaction and the contribution of this variable to the prediction in Figure 7.

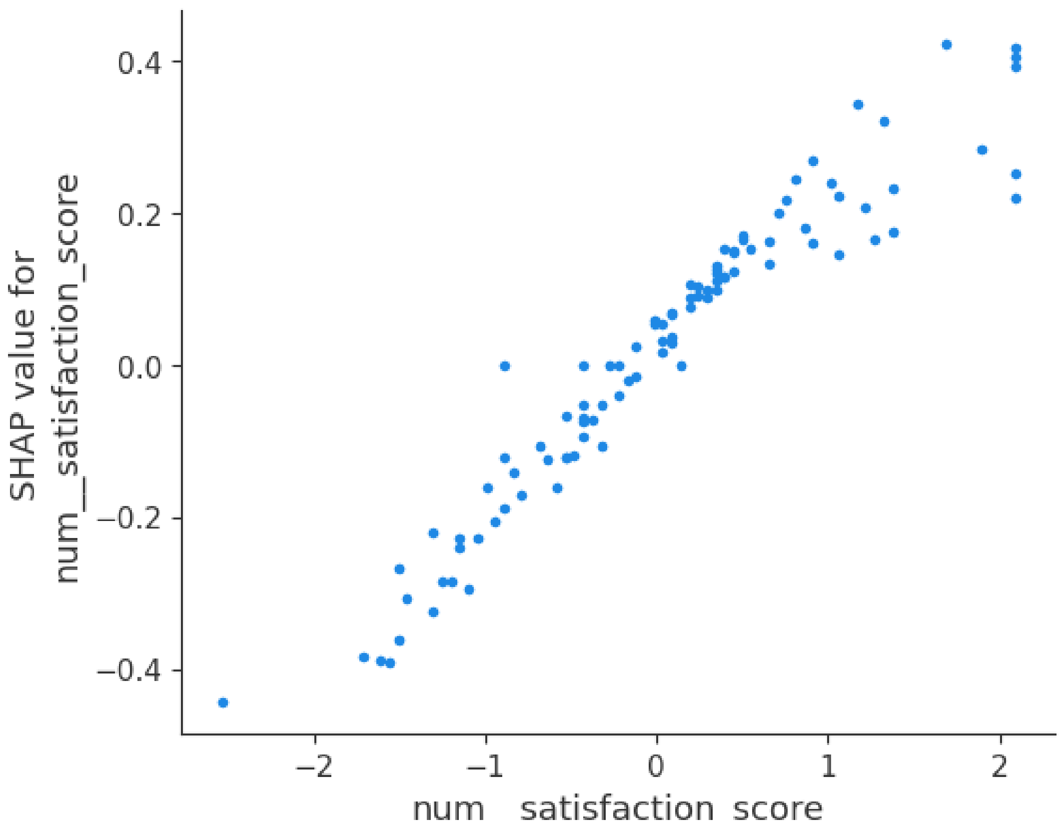

Figure 7. Satisfaction level and the contribution of the variable

The higher the stakeholder satisfaction, the greater the probability of project success. Conversely, budget overruns and significant delays negatively impact project success (See Figure 8).

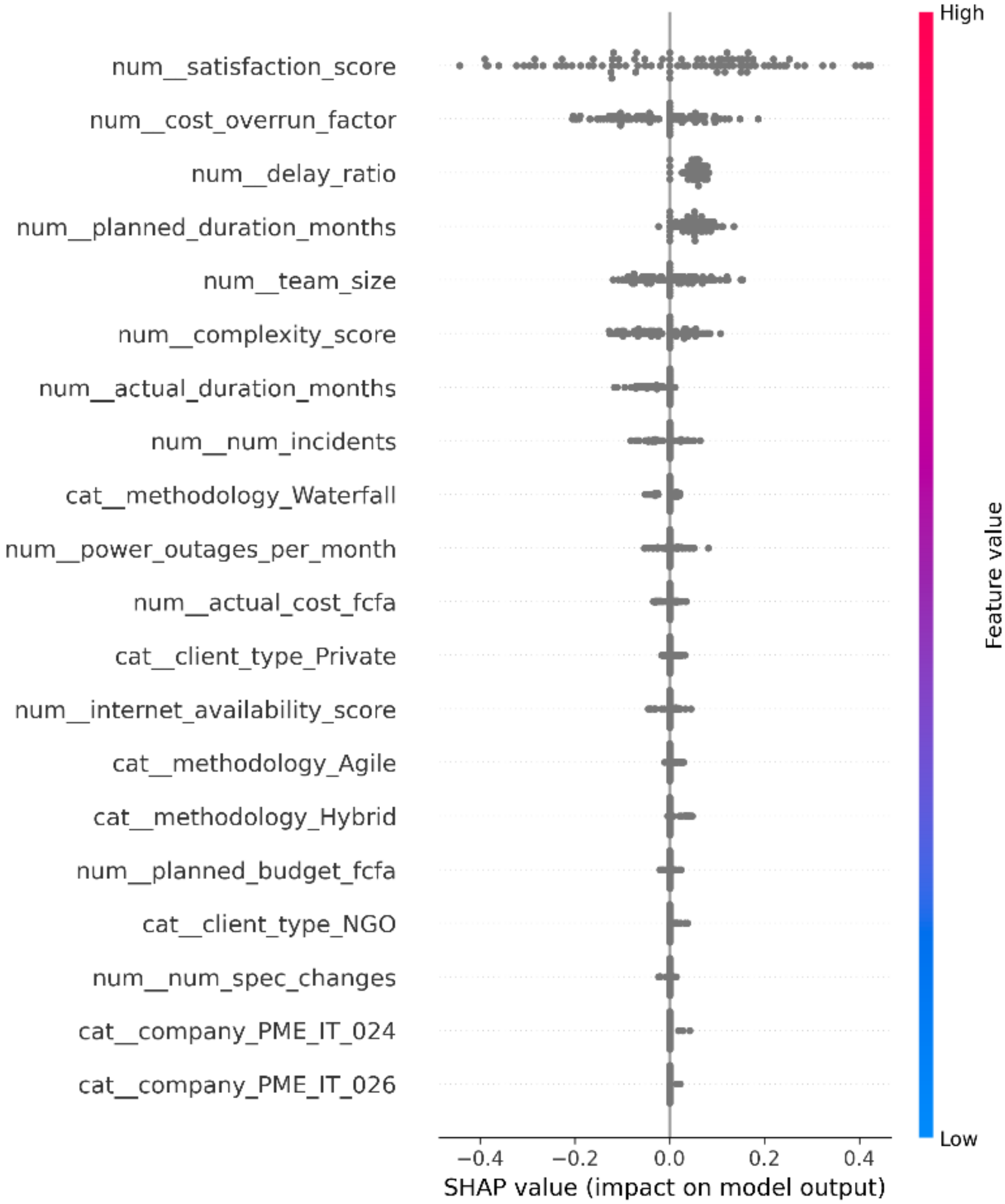

Figure 8. SHAP values analysis

The local analysis performed using the Waterfall diagram (Figure 9) illustrates the decision-making process of the model for a particular project.

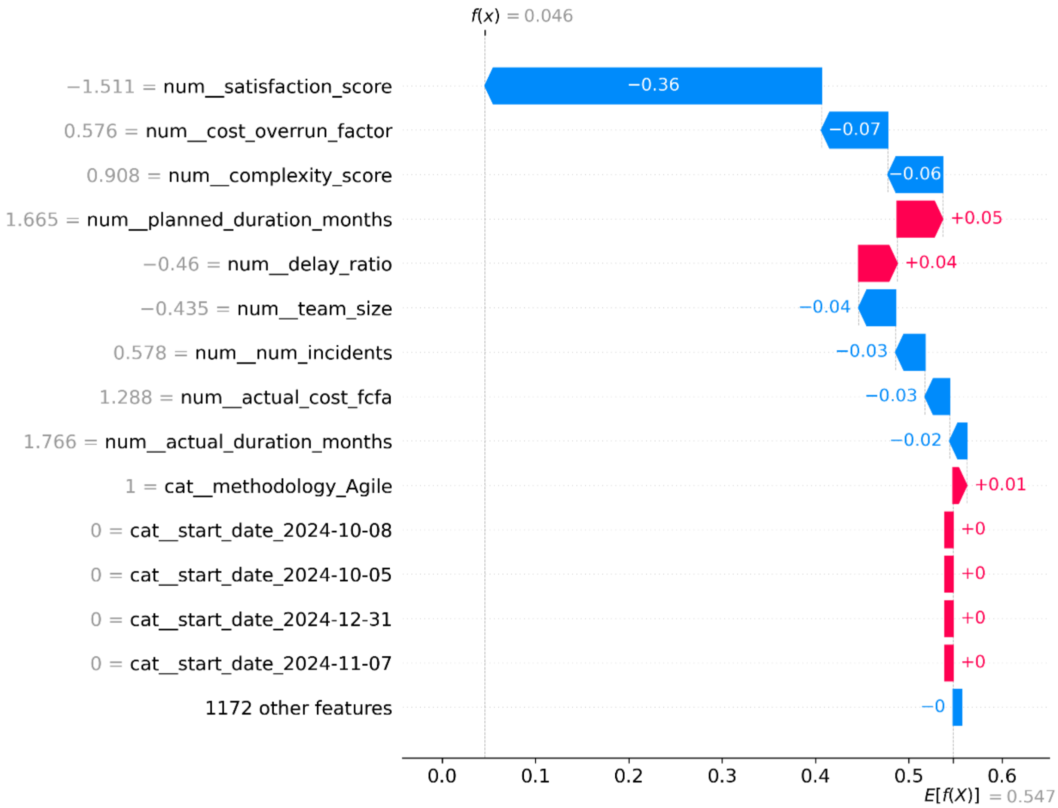

Figure 9. Waterfall diagram

In the example studied, a low level of satisfaction is the main factor reducing the probability of success. Budget overruns, project complexity, and accumulated delays also contribute to shifting the prediction toward a riskier situation, while certain factors, such as the planned duration, have a favorable effect. These results confirm the value of explainable artificial intelligence for improving the understanding of decisions produced by predictive models.

4.5. Analysis of Interactions Between Variables

The study of SHAP interactions (Figure 10) reveals that the planned and actual durations of projects exhibit interdependent behaviors likely to influence the probability of success.

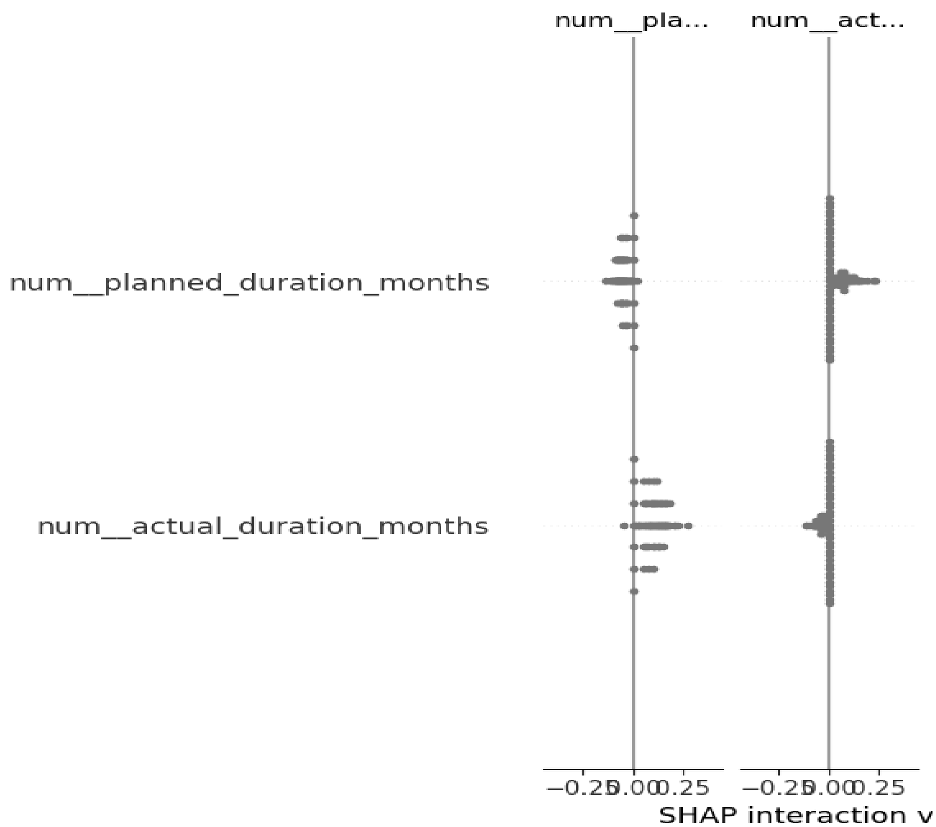

Figure 10. SHAP Interaction Analysis

This observation underscores the importance of rigorous schedule management and confirms the multidimensional nature of IT project performance factors.

4.6. Risk Distribution and Early Warning System

The risk probability distribution analysis reveals the existence of projects with varying levels of exposure. While a significant proportion of projects have a low probability of risk, several projects appear to fall into areas of higher vulnerability (Figure 11)

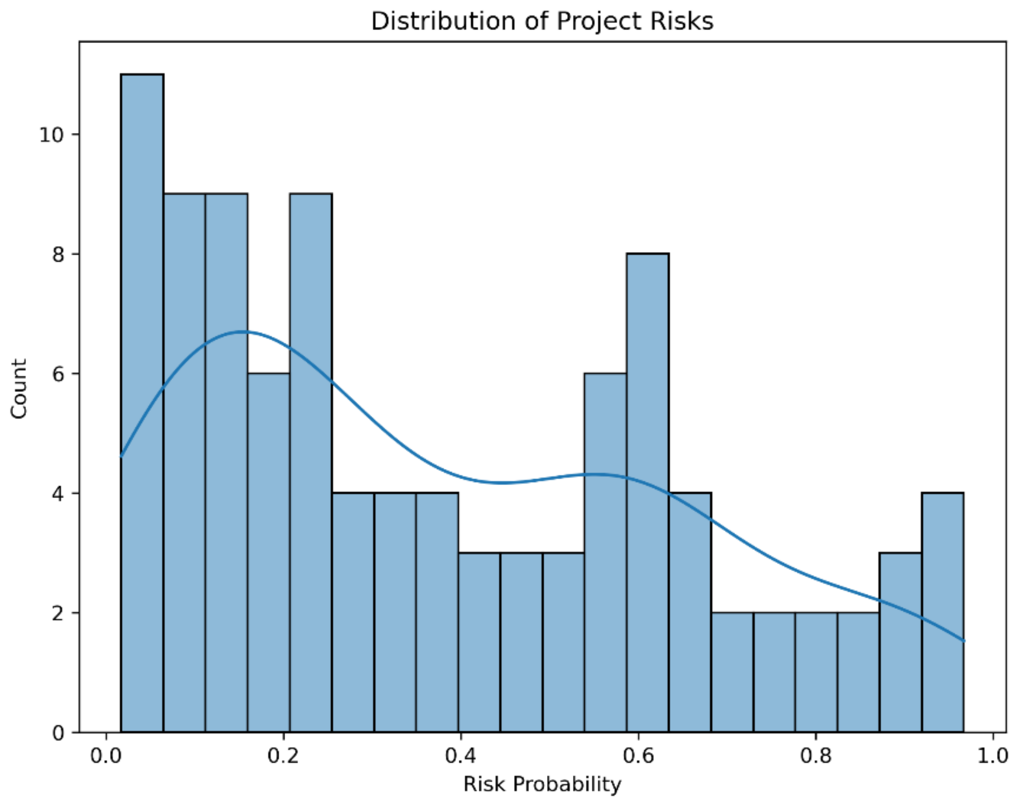

Figure 21. Risk distribution and early warning zones

This distribution confirms the relevance of the early warning system integrated into the developed prototype. It allows for the rapid identification of projects requiring special attention and serves as a decision-making tool for project managers and SME leaders.

Overall, the results demonstrate that combining machine learning techniques and explainable artificial intelligence not only delivers satisfactory predictive performance but also provides a transparent understanding of the factors influencing the success of IT projects in SMEs in Niamey. This approach thus paves the way for the development of intelligent management and proactive monitoring tools adapted to African digital environments.

5. Discussion

5.1. Performance of Machine Learning Models

The results obtained show that machine learning techniques are relevant tools for predicting the success of IT projects in SMEs in the city of Niamey. The seven algorithms evaluated demonstrated generally satisfactory performance, with the SVM model achieving the highest AUC-ROC value. This observation confirms the ability of supervised approaches to capture the complex relationships between the technical, organizational, and infrastructural characteristics of projects.

These results are consistent with the work of Bangarigadu and Nunkoo (2023), Razaghzadeh B. M. et al. (2024), and Nishat et al. (2025), which highlight the effectiveness of machine learning for predicting the performance of SMEs, startups, and digital projects. The similarity in performance obtained through logistic regression, Random Forest, and XGBoost also suggests a certain stability in the phenomenon studied and confirms the potential of nonlinear methods for improving risk anticipation.

5.2. Importance of Human and Organizational Factors

The analyses of the importance of variables and the results from SHAP reveal that the level of stakeholder satisfaction is the most decisive factor in the success of IT projects. Budget overruns, accumulated delays, project duration, complexity, and team size also appear as major variables.

These observations are consistent with classic project management principles and align with the results obtained by Razaghzadeh B. M. et al. (2024), according to whom resource-related and operational performance dimensions play a decisive role in the success of innovative projects.

5.3. Influence of Infrastructural Constraints

One of the main contributions of this study lies in its consideration of the constraints specific to the Nigerien context. The results highlight the influence of power outages and internet access availability on the performance of IT projects.
Although their contribution is less significant than that of organizational factors, these variables remain relevant. This observation demonstrates that models developed in more mature environments cannot be directly transposed to African contexts without taking local realities into account. It also underscores the importance of contextual factors rarely considered in international studies.

5.4. Contribution of Explainable Artificial Intelligence

Beyond predictive performance, this study highlights the value of explainable artificial intelligence in managing IT projects. SHAP analyses made it possible to identify the variables responsible for the predictions and to provide global and local explanations for the model's decisions.

These results corroborate the work of Haldar and Capretz (2023) as well as that of Santos et al. (2023), which highlight the importance of explainability in strengthening the trust and acceptability of predictive models. Local analysis conducted on selected projects shows that SHAP can transform a complex model into a genuine decision-making tool for managers and decision-makers.

5.5. Scientific Contribution of the Study

This research makes several original contributions to the literature. First, it represents one of the first applications of explainable machine learning to predict the success of

IT projects in the context of Nigerien SMEs. Second, it combines several complementary approaches, including machine learning, SHAP analysis, the study of variable importance, and an early warning system for project monitoring.

Third, the study focuses exclusively on the 488 projects identified in the city of Niamey, the main center of digital activity in Niger. This choice provides a relatively homogeneous environment and allows for results that can be directly used by local stakeholders. Finally, the integration of a prototype smart dashboard demonstrates the possibility of transforming scientific results into operational decision-support tools.

5.6. Managerial Implications

The results obtained have several practical implications for SME managers and project managers. The developed models can be used as early warning systems to identify projects at high risk of failure before significant deviations occur.

Identifying critical factors also allows managers to focus their efforts on the most influential dimensions, including stakeholder satisfaction, cost control, adherence to deadlines, and managing project complexity. Furthermore, providing an explainable dashboard promotes more transparent decision-making that is better adapted to the operational realities of SMEs.

5.7. Study Limitations and Future Prospects

Despite the encouraging results, some limitations should be noted. The study is limited to IT projects identified in the city of Niamey and does not cover all regions of Niger. The relatively small dataset size is also a constraint that may affect the performance of the models.

Furthermore, certain variables likely to affect project success, such as team experience, technical skills, and organizational governance aspects, were not included in the model.

Future work could focus on expanding the study scope to the whole of Niger and other West African countries, enriching the data, and integrating more advanced models. Leveraging real-world longitudinal data, combined with deep learning approaches, digital twins, and real-time monitoring systems, could further enhance forecasting and decision-support capabilities.

6. Conclusion, Limitations, and Future Directions

This study aimed to develop an explainable predictive framework capable of anticipating the success of IT projects in SMEs in the city of Niamey using machine learning techniques. Based on a dataset of 488 projects identified in the Nigerien capital, seven classification algorithms were evaluated and compared. The results show that the models considered possess satisfactory predictive capabilities, with the SVM exhibiting the best performance at an AUC-ROC of 0.850. Explainability analyses based on SHAP identified the main determinants of project success, including stakeholder satisfaction, budget overruns, delays, project complexity, and certain infrastructural constraints such as internet availability and power outages.

From an organizational perspective, this study highlights the crucial role of human and managerial factors in the success of IT projects and demonstrates that the specific constraints of African SMEs must be considered in project management processes. From a technological and infrastructural standpoint, the results highlight the significant influence of disruptions related to power supply and internet availability on the performance of digital projects. Methodologically, this research represents one of the first applications combining several machine learning algorithms, SHAP-based explainable artificial intelligence, temporal panel structuring, GroupKFold validation, and the development of an early warning system applied to the context of Nigerien SMEs.

However, some limitations must be noted. From an organizational perspective, certain variables likely to influence project success, such as team experience, technical skills, and organizational maturity, were not integrated into the model. Technologically and infrastructurally, the data used comes exclusively from projects identified in the city of Niamey, which may limit the generalizability of the results to other contexts. Finally, from a methodological standpoint, the relatively moderate size of the dataset and the lack of real-world longitudinal data are constraints that could affect model performance.

Future work could focus, from an organizational perspective, on integrating new variables related to governance, skills management, and the digital maturity of businesses. From a technological perspective, expanding the study area to include all of Niger and other West African countries will improve the representativeness of the models. Finally, from a methodological perspective, leveraging real-world longitudinal data, using more advanced deep learning models, and developing digital twins and intelligent real-time monitoring systems offer promising avenues for strengthening the resilience and performance of IT projects in African digital environments.

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Appendix 1: structured questionnaire to project managers

Section	Question Nº	Question	Response Type / Options
General Information	1	Name of the company (optional)	Text
	2	Position of the respondent	CEO; Project Manager; Technical Manager; IT Officer; Other
	3	Type of organization	SME; Startup; Public organization; NGO; Other
	4	Main activity sector	Software development; Telecommunications; Digital services; Information systems; Cybersecurity; Other
Project Characteristics	5	Project identifier	Text
	6	Project start date	Date
	7	Project end date	Date
	8	Planned duration (months)	Numeric
	9	Actual duration (months)	Numeric
	10	Planned budget (FCFA)	Numeric
	11	Actual cost (FCFA)	Numeric
	12	Team size	1–5; 6–10; 11–20; More than 20
	13	Project complexity level	Low; Medium; High
	14	Development methodology used	Agile; Scrum; Waterfall; Hybrid; Other
	15	Number of requirement changes during the project	Numeric
	16	Number of incidents encountered	Numeric
Infrastructure Environment	17	Average number of electricity outages per month	Numeric
	18	Internet availability level	Very low; Low; Moderate; High; Very high
	19	Stability of digital resources	Poor; Average; Good; Excellent
Project Performance	20	Delay level compared to the initial schedule	None; <10%; 10–20%; >20%
	21	Budget overrun level	None; <10%; 10–20%; >20%
	22	Progress rate at project completion (%)	Numeric
	23	Stakeholder satisfaction level	1 to 5
	24	Customer satisfaction level	1 to 5

Final Project Outcome	25	Was the project successfully completed?	Yes; No
	26	Principal reason for failure	Budget overrun; Delays; Technical difficulties; Lack of resources; Connectivity problems; Power interruptions; Organizational issues; Other
	27	Factor that most influenced the project outcome	Text
	28	Would an intelligent early warning system have helped?	Yes; No; Not sure
	29	Would you use an explainable AI dashboard?	Yes; No
	30	Additional comments	Text