



## Explainable AI for Data-Driven Predictive Modelling Agile Projects

Saniya Mulla<sup>1</sup>, Vaishali Pawar<sup>2</sup>, Vishal Dhavle<sup>3</sup>, Sanket Darade<sup>4</sup>

UG –Dept. of AI&DS, Dr. D. Y. Patil Institute of Engineering, Management and Research, Akurdi, Pune

<sup>5</sup>Mrs Deepali Hajare, Assistant Professor, Dept. of AI&DS, Dr. D. Y. Patil Institute of Engineering, Management and Research, Akurdi, Pune

<sup>6</sup>Mrs Ashwini Dhumal-Assistant Professor, Dept. of AI&DS, Dr D. Y. Patil Institute of Engineering, Management and Research, Akurdi, Pune

**Emails:** [saniyamulla172@gmail.com](mailto:saniyamulla172@gmail.com)<sup>1</sup>, [vaishupawar343@gmail.com](mailto:vaishupawar343@gmail.com)<sup>2</sup>, [vishaldhavle06@gmail.com](mailto:vishaldhavle06@gmail.com)<sup>3</sup>, [sanketdarade07@gmail.com](mailto:sanketdarade07@gmail.com)<sup>4</sup>, [deepalihajare1204@gmail.com](mailto:deepalihajare1204@gmail.com)<sup>5</sup>, [ashwini.dhumal7602@gmail.com](mailto:ashwini.dhumal7602@gmail.com)<sup>6</sup>

### Abstract

Agile software development projects generate massive amounts of data related to tasks, sprints, team performance, defects, and delivery times. While machine learning-based predictive models are increasingly being employed to predict project outcomes like effort estimation, sprint velocity, risk, and delivery delays, the lack of transparency in these models often results in a lack of trust and acceptance among the project stakeholders. This paper explores the application of Explainable Artificial Intelligence (XAI) approaches to enhance the explainability of data-driven predictive models in agile project management. The proposed framework combines predictive machine learning techniques with explainability tools to generate clear and understandable interpretations of the model's outputs. The model predicts the critical project matrix by analysing the historical data of agile projects from issue tracking systems and version control systems, and also explains how features such as team size, task complexity, sprint duration, and changes to the backlog impact the predictions. Techniques such as feature importance analysis and local explanation techniques in XAI are employed to ensure that the predictions are more interpretable and actionable.

**Keywords:** Explainable AI(XAI), Predictive Modelling, Agile Project management, decision making, predictive modelling, Data-Driven Decision Making.

### 1. Introduction

Agile project management has emerged as the most popular approach to software and information technology projects because of its focus on iterative development, flexibility, and continuous collaboration with stakeholders. By breaking down work into short development cycles, Agile project management tools help teams quickly react to changing requirements. However, Agile projects often face issues like sprint delays, failed goals, and project failure, which call for the need for efficient tools to track and forecast the status of projects at various stages of the project life cycle. Currently, Agile project managers extensively use descriptive analytics tools like Jira and Trello. Although these tools help track progress and visualise workload, they lack predictive insights and do not provide warnings about potential risks. Consequently, management actions tend to be more reactive than proactive,

making it difficult to address problems like deteriorating team performance, rising technical debt, or schedule delays before they impact project results. Recent advances in artificial intelligence and machine learning have enabled the development of data-driven techniques for forecasting outcomes in Agile software projects. However, most current models based on ML are black boxes, which provide no insight into the prediction process. However, the lack of interpretability is a barrier to adoption in a professional project management setting, where accountability and explainability are critical. This is where explainable artificial intelligence (XAI) comes in, which offers human-understandable explanations of model behaviour using techniques including SHAP(Shapley Additive exPlanations) and LIME(Local Interpretable Model-Agnostic Explanations), which are applied to interpret and

explain the model predictions. A systematic review of XAI in Agile project management was recently conducted, and it found that the lack of standardised Agile-specific indicators and the lack of empirical validation of explainable predictive models are some of the research gaps. To address these research gaps, an empirical study was conducted to show that combining artificial neural networks with explainability methods can provide high predictive accuracy and actionable insights for Agile project management. Based on these findings, this study aims to improve explainable and data-driven predictive modelling for proactive and transparent Agile project management

## 2. Methodology

### 2.1 Study Design and Data Source

This research uses a data-informed experimental design to forecast the status of Agile projects using machine learning and Explainable Artificial Intelligence(XAI).The dataset includes 360 finished Agile software projects gathered from the telecommunications industry. Each project entry represents sprint-level data and is categorised as Successful, Delayed, or Failed according to the time taken for project delivery, budget utilisation, and the accomplishment of sprint goals. Data preparation included standard normalisation and stratified train-test splitting (80% for training and 20% for testing), as done in previous research.

### 2.2 Feature Selection

22 indicators of Agile project performance were employed as input variables. These variables were previously determined by a literature review and validated by a Delphi method-based expert consensus validation. The variables are organized into four categories: Efficiency, Effectiveness, Endurance, and Complexity. Only validated variables were considered to ensure replicability.

### 2.3 Tables

Table 1 presents the selected Agile project features along with their definitions and measurement criteria. The table clearly summarizes the key performance indicators used in this study to evaluate project success. The feature selection process was carried out in a structured and transparent manner through literature review and expert validation.

**Table 1 Experimental Input Features for Agile Project Status Prediction**

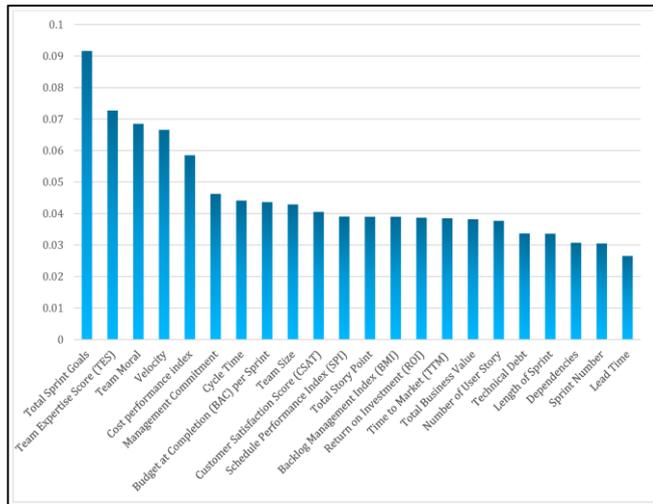
Category	Feature	Unit / Scale
Efficiency	Sprint Length	Weeks
	Lead Time	Days
	Cycle Time	Days
Effectiveness	Cost Performance Index (CPI)	Numeric
	Total Sprint Goals	Count
	Velocity	Story points
Endurance	Return on Investment (ROI)	%
	Team Morale	1–5 score
	Customer Satisfaction (CSAT)	%
Complexity	Team Expertise Score (TES)	1–10 score
	Technical Debt	Count
	Task Dependencies	Count
	Time to Market (TTM)	Days

### 2.4 Figures

The system architecture shown in Figure 1 is a general representation of an explainable AI-enabled Agile project management system. The user input provided by project managers is done through a web-based dashboard, which interacts with a backend API for data processing. The Agile project data can be sourced from tools like Jira/Trello and stored in a centralized database. The project status prediction is done by a machine learning model, and an explanation is provided by an explainable AI module (SHAP/LIME). The results are provided to the user as prediction output and explanation summary.



predictions is calculated using the gradients of the loss function with respect to the feature in the predictive model.



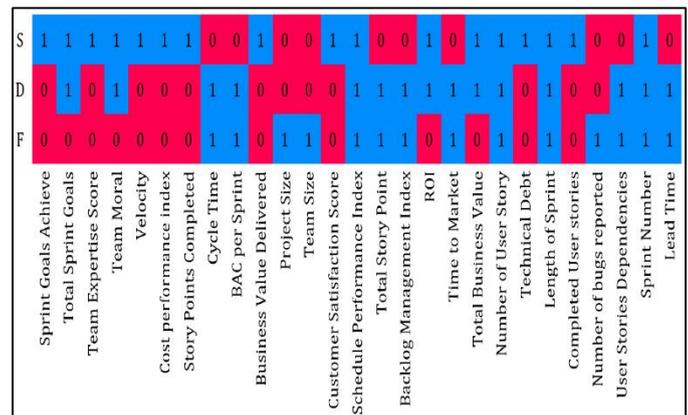
**Figure 4 Feature Importance Visualization for Predicting Project Status**

The findings indicate that the number of sprint goals, the Team Expertise Score (TES), and team morale play a major role in determining the success of agile projects. Well-articulated sprint goals help in steady improvement, and high team expertise helps in overcoming Agile project challenges. Moreover, high team morale boosts productivity, teamwork, and innovation, making it an essential ingredient in the long-term success of projects.

### 3.2 Discussion

This section discusses the behaviour of project features for various project categories using association rule mining. After predicting the project status using an artificial neural network and understanding the importance of various features using SHAP, the Apriori algorithm is used to study the behaviour of features for various categories based on their average feature values. Figure 5 shows how feature values for each category are above or below the average. Successful projects (Category S) are typically smaller in size, with compact teams. Successful projects have the advantage of experienced teams, high velocity, and high team morale, which help in completing projects on time. Delayed projects (Category D) are larger in size and more complex, with larger teams and lower

performance levels; although they have high value potential, they are often plagued by schedule overruns. Failed projects (Category F) are marked by significantly longer schedules, larger team sizes, and lower team experience and productivity.



**Figure 5 Behavior of Features in Each Category of Projects**

### Conclusion

This study aims to develop an accurate and dependable model for predicting project performance to evaluate the status of projects in the telecommunication industry, which has project outcomes categorised as successful, delayed, or failed. Based on the Agile Project Management methodology, 13 validated features regarding efficiency, effectiveness, and endurance were identified in 360 actual projects in the telecommunication industry. The results emphasise team-related aspects, specifically team expertise and capability, as the most important factors for project success. An Artificial Neural Network (ANN) was designed and trained to forecast project results, and its architecture was optimised using Neural Architecture Search (NAS). To improve interpretability, the SHAP algorithm was employed to explain the predictions of the model, allowing for a better understanding of the impact of the individual variables on project performance. Moreover, the Apriori algorithm was employed to examine behavioural patterns for different categories of projects. The proposed model showed excellent predictive accuracy, with strong performance in terms of accuracy, precision, recall, and F1-score



metrics. Although the results confirm the effectiveness of the proposed method, the study is restricted to software and telecom projects. Future studies attempt to validate the proposed model on other domains and examine hybrid approaches, such as fuzzy inference systems and data envelopment analysis, to further enhance predictive accuracy.

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