Using Artificial Intelligence to Detect Underlying Issues in Projects: Seeing Beyond Current KPIs and Project Status Reports

Research-in-progress

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Abstract

Project status reports traditionally are the primary source of project control. However, they offer an incomplete view relying on static snapshots with limited historical context for managing projects.. This study explores the research question that past project performance can inform future insights, the need for which is driven by increasing workloads and the rise of artificial intelligence (AI). Project professionals face an immense pressure to deliver increased business value with limited resources, which provides a motivation for improved ability to predict project outcomes. The objective of this study is to understand the application of AI to reduce the burden of analysing a large data source that changes over time, and to identify potential upcoming challenges in delivering successful projects outcomes. Using a machine learning approach, this study offers insights into detecting patterns and relationships in project data indicating success/failure and outline the criteria for a successful AI-enabled project management system.

Keywords: Artificial Intelligence, Project Management, Prediction, Random Forest, Project Status

1 Introduction and Background to Study

Typically, a project has been defined as a unique set of coordinated activities. A project has definite starting and finishing points, undertaken by an individual or organization to meet specific objectives within defined schedule, cost, and performance parameters (Lester 2006). To deliver a project in a successful way, management of the project is required. As noted by Klojcnik et al. (2018) to manage a project successfully, project management is important and it is defined as "planning, organizing, directing, and controlling of company resources for a relatively short-term objective that has been established to complete specific goals and objectives." Despite project management concepts and techniques being well established in industry, the Standish Group CHAOS report continues to report high failure rates, with only 16.2% of IT projects being on time and budget with all promised scope (Kumar 2021).

Munns and Bjeirmi (1996) have shown that project management leads to project success through the application of project management techniques. This is often the domain of the project management office. However, Haji-Kazemi et al. (2015) have shown that there are many barriers to detecting early signals of project failure including time pressure. Most organisations are simply too busy dealing with project issues to be able to analyse the details of projects and proactively detect future problems. As such, this study attempts to enhance the ability to increase project success through the application of artificial intelligence (AI). The study hypothesizes that AI applications can provide assistance to project officers to manage time pressure, manage project goals, and detect failure signals.

Lester (2006) implies that project success relates to the schedule, cost, and other parameters. This is a traditional definition of project success. However, despite the application of project management techniques, historically projects fail as has been tracked by the Standish Group over years (Kumar 2021). This has led to an awareness that project success may need to be redefined. Othman et al. (2018) have shown that the concept of monitoring signals for early warning signs in different forms can lead to increasing project success through early intervention. A key research question of this research is that there are many potential warning signals for emerging problems in projects but as project staff are so busy, assistance is needed. AI such as can play an important role in detecting emerging problems and making sense of them and knowing which ones to focus on.

To know what to focus on it is important to know what project success actually means. Bang et al. (2022) and Radujković and Sjekavica (2017) have shown however that there is no way to have consensus as to what project success consists of, but through the actions of project management staff success is more likely. As such, this study explores the research question that a model of early warning of failure is required that can learn from multiple signals and is not dependant on a rigid definition of success. Rather the need exists to allow the organisation to define project success and provide the signals, and artificial intelligence is able to learn from this to detect signals that the project staff cannot detect until too late. Nikander and Eloranta (2001) have laid the groundwork by establishing the concept of early warning and a flexible approach being needed. This research aims to take a practical step and utilise AI to provide project managers with early warning signals of impeding project failure. Can we learn from past results to predict future project success? Project organisations do not typically have the data or organisational knowledge to have memory of past lessons, and therefore cannot apply learning to detecting failure signals in future projects. The key question of this research is, can we use machine learning to analyse the embedded project knowledge that a project in an organisation would need to analyse to detect an issue before it transitions into project failure?

Specifically, this study attempts to learn from signals of change in a project, where a current status report may show a particular set of indicators such as a green traffic light representing the project status, but this light has been alternating between red and green each reporting period for the life of the project, indicating there is actually an underlying problem with a project. By following a design science approach and utilising machine learning techniques this study attempts to answer this contemporary research question: to determine if patterns in the status of other projects, in effect learning from past projects, could be used to predict the success of future projects?

This paper is structured as follows. The relevant literature is reviewed next highlighting the gap in the literature and knowledge regarding of use of artificial intelligence to predict project failure. The method followed is provided next. Then key findings of the study so far are provided. Then the conclusions and implications of the study for theory and practice are provided. Furthermore, the limitations of study as well as the future research areas are noted.

2 Literature Review

A review of the literature was conducted by searching Web of Science, Science Direct, ResearchGate, and Google Scholar for combinations of the keywords "project, prediction, artificial intelligence, predicting success, predicting failure, early warning, signals". A limited number of publications were found that explicitly provide information on prediction of project success using AI. Most publications take a theoretical approach to reviewing literature or putting forward possible solutions, without testing the approaches.

Vajjhala and Strang (2024) in a literature review concluded that there are a few studies where researchers applied machine learning to predict project success, rather more specific approaches were taken such as using machine learning to analyse project scheduling. Uddin et al. (2021) surveyed the general concept of machine learning in analysing project performance, which is an aspect of detecting early signals of failure. Suma et al. (2014) specifically focussed on the use of the random forest classifier in predicting software project defects. Furthermore, Vajjhala and Strang (2024) specifically focussed on the use of the random forest classifier in predicting military IT project success of external contract companies but through the lens of using machine learning to mine big data to identify the reason for failure of projects.

The gap identified in the literature and through industry expert input points to existing approaches, where they exist, being hardcoded to the status indicators and status reports that the project organisation has thought to check. These are static, meaning that they do not take historical status into account. There has been no related research into education sector projects found. In addition, the research is not internal focussed, but rather on companies completing projects for clients across mostly construction, military or IT projects, where the IT projects are analysing very specific aspects such as schedules only. Specific research into predicting project success generally focus on construction. Articles on using random forest are mostly for predicting software project success. This has shown us that a gap exists for an approach to predict project success from historically changing project status, as well as understanding the use of the machine learning random forest classifier to achieve this. Existing usage of artificial intelligence applied to project management, identified in the literature review, focusses two main areas. The use of language models for providing assistance in the use of processes, and machine learning for the use of predicting cost estimates in the construction industry.

3 Method and Approach

The study approach is grounded in design science, an iterative research methodology that seeks to create and evaluate artifacts—such as models, methods, or systems—designed to solve identified problems (Carstensen and Bernhard 2019). The process begins with the awareness of a problem, which, in this case, has been informed by industry experts through the formulation of a research question. Solutions are proposed by drawing on existing theoretical foundations and prior research, identified through a thorough literature review. A prototype or artifact is then developed based on these suggestions and evaluated through rigorous testing. This iterative process not only aids in refining the artifact but also in generating new theoretical insights. The goal is not merely to develop a practical solution for industry but to contribute to the broader body of knowledge concerning predicting project success and failures, a key requirement of design science research as emphasized by Gregor and Hevner (2013).

The prototype was built using the Python Sklearn random forest classifier. As input, we used data from the last 12 months of projects from a leading Australian university. This represented 73 projects and their status and other fields (features used in the random forest). The projects were from a leading Australian university, in the domains of technology, buildings, and business transformation with budgets of over $1,000,000 Australian dollars. The projects are governed by a central Project Management Office. A goal of this research is to provide the Project Management Office in an organisation with improved insight and early warning into potential failures of the projects.

The research question points to a need to learn and predict, not only explain why a project failed. The input to the research question is a list of projects that have already been labelled as succeeding or failing through a project post implementation review. The goal is to discover the signals that support such a human applied label, and then build a model to predict the failure of future projects. As a result, both supervised and unsupervised machine learning choices such as neural networks, random forest, cluster analysis and k-means analysis are suitable as described by Vajjhala and Strang (2024).

The machine learning (ML) technique, Random forest classifier is a simple to understand predictive model that can be conceptually explained in relation to how groups of humans may make decisions. Vajjhala and Strang (2024) explain that a few researchers have argued that machine learning is better than traditional decision making in project risk management as it reduces human bias. In this research we propose that a random forest model is most suitable as (1) it is simple to understand (2) it is understandable to business users, (3) can deal with categorical data and (4) is resistant to bias and learning noise in the data. A brief trial of other classifiers including support vector machines and a simple neural network was conducted but the results were not sufficiently promising to motivate including these other classifiers in the initial pilot.

After cleaning the data of 73 projects 14 initial features were selected for training the random forest model. These features were static, such as the name of the project sponsor, or the current red/amber/green status. These features were available for 12 months, providing us with the basis to define trends. An interative process of feature selection was carried out to identify which features provided the greatest contribution. It was found that an increased number of features (status data points) did not increase the model's predictive ability. Further dynamic features were then derived for example the rate of change of a red/amber/green status, or the number of times a project manager was changed on the project. This moved us from the static to a more dynamic view. The dynamic features represent the change over time, for example the project manager (static) changed several times, and the feature is the measurement of that change (dynamic). It is the learning gained from applying these more dynamic features that supports the aims of this research, where we feel that we can predict potential project failure from a combination of the changes in the static features over time. After engineering dynamic features, we had 11 features to work with.

The data set for 73 projects available for exploring our research question was split 80/20. Eighty percent were used for training and 20% were used for testing, 46 projects were labelled as failure and 27 projects as successful. A random forest classifier was applied, with the label of success/failure.

While an out of the box random forest does not need to be hyper-parameter tuned, (Bernard et. al, 2009) have shown that advantages are available through tuning. A grid search was run using input values of 'n_estimators': [50, 100, 200], 'max_depth': [None, 10, 20, 30], 'min_samples_split': [2, 5, 10]. This determined the following were the most successful parameters: 'max_depth': None, 'min_samples_split': 5, 'n_estimators': 200, with a random state of 42.

4 Findings: Random Forest Model

The random forest model allowed us to determine the relative importance of the features as shown in Table 1. The Relative Feature Importance column represents the relative importance of each feature in determining the outcome of the model's predictions. Higher values indicate that a feature has a stronger influence on the model's decisions, meaning it plays a more significant role in predicting project success. The scores are normalised to sum up to 1. By focusing on the top features, the model can be optimized for better performance, allowing project managers to prioritize key factors that have the most impact on the likelihood of a project's success.

Feature #	**Feature**	**Description**	**Relative Feature Importance**
1	Number of active months	The duration in months of the project	0.265
2	Monthly rate of red/amber/green change	The frequency of change per month	0.185

3	% time in delivery phase	The percentage of total duration in a specific phase (delivery)	0.167
4	%time in Complete phase	The percentage of total duration in a specific phase (Complete)	0.12
5	Number of times PM changed	Count of the changes in project manager in 12 months	0.08
6	Number of project phase changes in 12 months	Count of the number of times the project changed overall phase in 12 months	0.06
7	% time in Planning phase	The percentage of total duration in a specific phase (Planning)	0.06
8	Number of red/amber/green changes	Number of status changes between red/green/amber in 12 months	0.03
9	% time in Concept phase	The percentage of total duration in a specific phase (Concept)	0.00
10	Number of times Sponsor changed	Count of the changes in project sponsor in 12 months	0.00
11	% time in Initiate phase	The percentage of total duration in a specific phase (Initiate)	0.00

Table 1. 11 Project status features relative importance determined by random forest classifier.

The findings are interesting as they show that a mixture of static and dynamic features are driving project success, but the static features such as Number of Active Months themselves are related to time. By examining the results, we were able to conclude that the proof of concept was successful and worthy of further research. Precision and recall were the measures used to evaluate the performance of the random forest model. Precision and recall are the most commonly used measures for pattern recognition applications (Franti and Mariescu-Istodor 2023). Precision is the number of correctly predicted results (true positives) relative to all predicted correct results. Recall is the number of results relative to the number of expected results for each class. The results are summarised in figure 1 below. A high precision, of 82%, was achieved. This indicates that if a project is flagged for potential failure, it is 82% likely to be correct. However, recall was only 50%. This indicates that 50% of projects that should have been predicted to fail are not being detected. This is not considered a blocker at this point as: the amount of data is limited; and the nature of the problem needs to be considered in more detail in order to specify more precisely, the important features for predicting project failure. While we would prefer to have a high recall as well, we feel that project staff would rather have some warning than none.

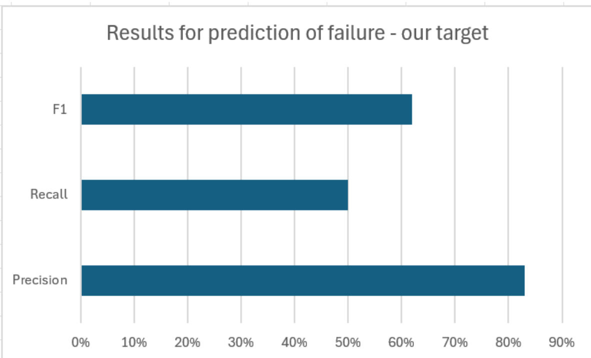

Figure 1. Summary of results for prediction of failure

The features that contributed the most to the result will depend on the specific data used in each organisation. The most important feature was the duration of the project. Next most important feature was the rate of changes of the red/amber/green traffic lights, which was expected. It is important to note that organisations will need to repeat this process with their data, as they may have different features. You need to take a fresh approach for your own data, and not consider this approach, as a plug and play solution.

5 Conclusions

We have shown that it is possible to predict the success or failure of a project using an artificial intelligence technique – random forest classifier, which will provide an early warning for project organisations as to which projects should receive further attention. The research question investigated was to determine if patterns in the status of other projects, in effect learning from past projects, could be used to predict the success of future projects. This is proven to be possible through the use of a random forest machine learning classifier. We used static project data such as the current red/amber/green, and then derived further dynamic features relating to how data/status of a project changed over time. Each project was labelled through a manual Post Implementation Review. The snapshot project data over time, and the known success or failure was used as input to the random forest to create a model to predict future success or failure of a project. In this way we are able to represent the experience of project staff in identifying projects that may fail, without them needing to dedicate the time to review each project. The model was successful in that it had a high ability to be correct in the projects it flagged for review, although it did not flag all of the projects that we would have liked. As a proof of concept the approach has proven viable.

This research forms part of a wider study into the application of AI to improving project management. Currently a cycle of literature review, gap analysis and artefact development is underway, as described in the Approach and Method section. Within this a theme of prediction of project success/failure is being explored. In literature there are few practical examples of using AI for predicting project success, but no studies were found that specifically focus on the nature of change to the project status over time as viewed by a project management office. The studies identified so far such as Vajjhala and Strang (2024) specify a list of features that should be analysed to predict project success but these relate to static attributes of the project such as the experience of the project manager and the size and complexity of the project. The key focus of this research: Is can project success be identified through creating a new signal, specifically due to change of for example: the project manager, sponsor, or frequency of change of the status traffic light of the project. In addition, this work leads to a contribution to the understanding of using machine learning for predicting project success using a random forest model, in the context of the education sector. The focus of this research is on development and evaluation of a practical artefact, an AI application for predicting project failure which is then analysed to derive further theoretical and practical contributions.

This research was completed with a limited dataset. Random forests will generally perform better with more data. With only 73 projects the model may not have sufficient data to be able to fully capture the underlying patterns and relationships in projects. Discussions with another university are underway, and a proposition has been made to several other universities to gauge interest. As such, expansion of data would add more reliability and credibility to this model.

The proof of concept has focused on the model, but not yet on where it will be used. Human factors need to be considered when the results of the AI suggestion are presented, as users may not appreciate being told their project is going to fail by a machine. In future we want to survey project staff on the level of accuracy that they would require to trust the output of an AI application to make decisions on project management – success or failure.

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