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PROJECT PERFORMANCE PREDICTION BASED ON MACHINE LEARNING: A SYSTEMATIC LITERATURE REVIEW

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Abstract:

Context: For successful project management, it is crucial to accurately predict project performance, as this enables effective resource allocation and proactive decision-making. Traditional approaches often fail to achieve this effectively, leading to increased interest in using machine learning techniques due to their reliable predictive capabilities. **Objective:** This research study conducts a systematic literature review on predicting project performance to examine the current studies on machine learning applications. **Methodology:** This systematic review employs the PRISMA technique to analyze 34 relevant studies from the Scopus, IEEE Xplore, and PubMed databases, published between 2015 and 2024. This study presents three research questions that examine trends in project performance based on machine learning studies, identify the machine learning models most frequently used in the context of project performance, and explore their applications in various project contexts. **Findings:** The findings indicate that research trends increased from 2020 onwards, with support vector machines and artificial neural networks being the most commonly used models among machine learning models in the context of project performance. It also found that most research conducted in the software and construction industries utilized time and cost-related features, with only one study observed in the context of a student project. **Conclusion:** The findings of this study confirm that the machine learning approach has strong potential to increase prediction accuracy in project management across different project contexts. This systematic review presents a comprehensive

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taxonomy of machine learning techniques and identifies key research gaps. It highlights the need for validating machine learning models in real-world contexts and also introduces hybrid models that can integrate human expertise. This study is a valuable source that may help practitioners and researchers leverage machine learning in the project domain.

Keywords:

Machine Learning; Project Management; Project Performance; Systematic Literature Review; Support Vector Machines; Artificial Neural Networks

Introduction

Project performance (PP) prediction has become the subject of modern research in the project management (PM) domain. PM is a formal discipline and a common technique of work organization, but surprisingly, it did not emerge before the 1950s (Hodgson & Cicmil, 2006). At that time, the United States Department of Defense started working on incredibly massive and complicated projects, like the Apollo moon program and the Polaris submarine. To assist these programs, new innovative scheduling techniques were developed. The most important of these was PERT (program evaluation and review technique), which provided a probabilistic approach to estimating the duration of a project (Weaver, 2006). However, there is ongoing discussion on the real effectiveness of these approaches on the Polaris and Apollo programs (Koskela & Howell, 2002).

Previous research on the evaluation of PP has employed different techniques that rely on different sets of factors and evaluation measures. For example, EVM (earned value management) is a traditional technique used by project managers, program managers, and other high-level managers to monitor, visualize, and evaluate the project's status throughout its life cycle (Salari & Khamooshi, 2016). Another method to assess the overall PP is MDM (multi-criteria decision-making), which has been applied in various contexts to aggregate multiple performance measures (Barfod, 2012; Marques et al., 2011; Pillai et al., 2002). Data envelopment analysis, a performance evaluation technique that considers both independent and dependent variables, has been widely used to assess the relative efficiency of completed projects (Busby & Williamson, 2000; Cao & Hoffman, 2011; Eilat et al., 2006; Farris et al., 2006; Linton & Cook, 1998; Revilla et al., 2003; Verma & Sinha, 2002; Vitner et al., 2006).

These traditional techniques might not be enough to capture every aspect of a project. For instance, the EVM method considers project schedule and cost deviations; PP can also be affected by many other factors. A study suggested that in the context of PM, new techniques are required to predict PP based on several multiple criteria (Marques et al., 2011). Multiple criteria techniques consider a variety of criteria when evaluating a PP, but these are often dependent on the subjective preferences of the decision-makers. Moreover, the basis of these techniques is selecting the most suitable decision among several potential choices. However, decision-makers may not have considered all possible criteria and options when creating the different potential decisions. Since the data envelopment analysis method is viewed as a benchmark for evaluating the PP, it also has drawbacks. Because every project is different, a decision or set of criteria that works effectively for one might not be appropriate for another. A drawback of these techniques is the need to improve the prediction of PP in the context of PM (Cheng et al., 2010).

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Today, the world is undergoing a digital transformation, so the boom of machine learning (ML) technology is pervasive in every field due to the availability of a huge amount of digitized data, including information technology, engineering, marketing, education, healthcare, and PM (Malik et al., 2022). It provides a new and advanced approach to accurate prediction and intelligent automation. ML was initially grounded in pattern recognition and statistical learning. Now, it has rapidly grown with the increased availability of huge amounts of data, enhanced computational power, and more powerful deep learning models, enabling it to have a more robust analytical capacity (Razzaq & Shah, 2025). Therefore, it has become a fundamental part of modern and advanced predictive modeling. Due to its effectiveness, it is recognized as a central methodology in contemporary research, including PP prediction, where it can capture complex and nonlinear trends and generate reliable and meaningful insights. It offers clear advantages over traditional methods (Chan, 2022). So, professionals and researchers have utilized this technique to enhance decision-making, minimize time and cost consumption, increase efficiency, automate tasks, and facilitate various aspects of life (Aly, 2022; Osborne et al., 2022; Yagoub et al., 2021). Significant developments have been observed in ML predictive modeling, which can contribute to enhancing the prediction power of PP (Sadeghi, 2024).

The ML approaches have been extensively applied in PM to enhance different aspects, such as resource optimization, risk assessment, and cost estimation (Gil et al., 2021; Hashfi & Raharjo, 2023). From the perspective of PP prediction, ML techniques have shown reliable and accurate results based on project characteristics and historical data (Kerzner, 2023; Odejide & Edunjobi, 2024). Many researchers have utilized ML-based algorithms to address PP-related issues (Bilal et al., 2019; Uddin et al., 2024). For example, a recent review article identified that ML is the most commonly used artificial intelligence (AI) subfield in the context of PP prediction and algorithms, such as artificial neural networks (ANN), which were frequently used (Su & Ayob, 2025). Another study showed that ML supports project analytics within a data-driven framework (Uddin et al., 2022). In the R&D project context, the findings of the study indicated that AutoML-based approaches outperform traditional supervised ML models (Jang, 2022). Another study investigated the ML application to determine the selection of R&D projects, and the decision tree (DT) C5.0 model outperformed, which can inform the project selection decisions at the portfolio and organization level (Yoo et al., 2023). A multilayer perceptron (MLP) classifier achieved high accuracy in a construction project (Fan, 2025). A study showed that the random forest (RF) model performed well in predicting the success of startups (Razaghzadeh Bidgoli et al., 2024). A study by Sabahi and Parast (2020) showed that linear regression (LR) with lasso outperformed other models in predicting the students' PP. These empirical studies provide evidence of the application of ML in PP prediction. However, they vary considerably in scope, in terms of the use of different ML models, the kinds of projects considered, and the depth of comparative analysis. Therefore, the literature is fragmented and has substantial gaps.

There are several notable gaps in the above fragmented studies. Many of them focused on a specific project type, such as academia, construction, R&D funding projects, and startups, but do not offer a comparative analysis across different industries. As observed in the systematic review study by Su and Ayob (2025), there is a limited analysis of how the performance of ML varies across different project types, suggesting that many real-world project contexts are still unexplored. Additionally, it is worth noting that the aforementioned empirical studies yield promising results. For example, the AutoML and DT model outperforms in R&D, the MLP outperforms in the construction industry, and the LR outperforms in predicting students' PP in

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an academic context. However, they did not provide a comprehensive meta-analysis by comparing various ML models across different datasets from various projects, in the context of understanding the real strength of the particular model in a broader sense. Moreover, most studies remain technical and do not adequately discuss how their selected ML models can be applied in real-world PM practices, particularly across different industrial contexts that reflect real-world applications of the models.

These substantial gaps motivate the present systematic review study, as there is a need to thoroughly assess ML-based PP prediction research across different project types and methodologies. This study aims to display broader and more meaningful statistics regarding ML-based approaches for PP-related issues and linked research trends. The findings of this study will contribute to the development of the PM field and provide a structured overview of the existing data-driven solutions used to predict PP in different industrial contexts. The following are the research objectives of this systematic literature review (SLR):

- To identify the research trends in PP that use ML-based studies.
- To identify the most used ML models in the context of PP.
- To highlight the different contexts of the project that used ML-based studies.

The remaining sections of the paper are organized as follows: Section 2 presents the methodology, including the research questions and model development. Section 3 discusses the results, including the comparisons of the ML models. Section 4 provides a detailed discussion of the study's findings. Finally, Section 5 concludes the study by summarising the research's contributions and presents the future research directions in the context of PP.

Methodology

Search Strategy

The SLR follows the PRISMA strategy (Veroniki et al., 2025). Scopus, IEEE Xplore, and PubMed databases are used in this study. The reasons for selecting these databases are to ensure high-quality coverage of multidisciplinary, comprehensive, technical, and applied research, as well as an extensive number of peer-reviewed articles relevant to the context of PP-based studies. The search strings used in this study are presented in Table 1.

Table 1: Search Strings For Selected Databases

Database	Search String
Scopus	(TITLE-ABS-KEY("Project Performance") OR TITLE-ABS-KEY("Project Outcome") OR TITLE-ABS-KEY(Project)) AND (TITLE-ABS-KEY("Machine Learning") OR TITLE-ABS-KEY(ML) OR TITLE-ABS-KEY("Deep Learning") OR TITLE-ABS-KEY(DL) OR TITLE-ABS-KEY("Artificial Intelligence") OR TITLE-ABS-KEY(AI))
IEEE Xplore	("Project Performance" OR "Project Outcome" OR Project) AND ("Machine Learning" OR ML OR "Deep Learning" OR DL OR "Artificial Intelligence" OR AI)
PubMed	("Project Performance"[Title/Abstract] OR "Project Outcome"[Title/Abstract] OR Project[Title/Abstract]) AND ("Machine Learning"[Title/Abstract] OR ML[Title/Abstract] OR "Deep Learning"[Title/Abstract] OR DL[Title/Abstract] OR "Artificial Intelligence"[Title/Abstract] OR AI[Title/Abstract])

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Inclusion And Exclusion Criteria

The search results were not limited to a specific country. This study only considered articles published between 2015 and 2024. Articles focusing on ML-based PP studies were selected. Moreover, articles written in the English language were selected. Table 2 illustrates the exclusion and inclusion criteria for the selected studies.

Table 2: Inclusion And Exclusion Criteria For Selected Articles

Collection Criteria	**Inclusion Criteria**	**Exclusion Criteria**
Publication Time Range	Articles published between 2015 and 2024	Articles published before the year 2015
Publication Coverage	Worldwide	NA
Publication Language	English only	Articles published in languages other than English
Publication Type of Articles	Journal papers, review papers, and conference papers	Articles other than journal papers, review papers, and conference papers
Factors	PP-based factors	All other factors, excluding PP-based factors
Technique	ML-based techniques	All other techniques, excluding ML-based

The selected articles were studied using these exclusion and inclusion criteria. Firstly, the studies were examined by their title and considered whether the PP-related factors and ML, DL, or AI words were shown. Secondly, the abstracts of the selected articles were studied, and only those that were written in English and used ML-based models for PP were considered. The complete article was analyzed in the next stage to verify that the ML-based model accurately predicts the PP.

Screening Process

The results of the search string and the process of selecting studies are shown in Figure 1 of the PRISMA flow chart. Eight hundred seven articles were identified from the three databases (Scopus: 300, IEEE Xplore: 400, and PubMed: 300), and except for these, no additional records were selected. After removing the duplicate studies, only 521 remained. After reviewing the titles of the studies, 298 articles were removed. In the next step, only 78 articles remained after screening their abstracts.

Research Question Formulation

In this SLR, the motivation is to explore ML-based algorithms in the context of PP. The research aims to find ML models that effectively predict the PP. The article aims to present various statistics in the same context by examining relevant research studies. The study questions will examine the different trends, project context, and study purposes, and identify the research gaps in the PP context using ML. The lens of this systematic study will be performed by the following questions (RQs):

- RQ1: What are the research trends in PP that use ML-based studies?
- RQ2: Which ML models are most frequently applied in PP studies?
- RQ3: In which project contexts have ML-based techniques been frequently used?

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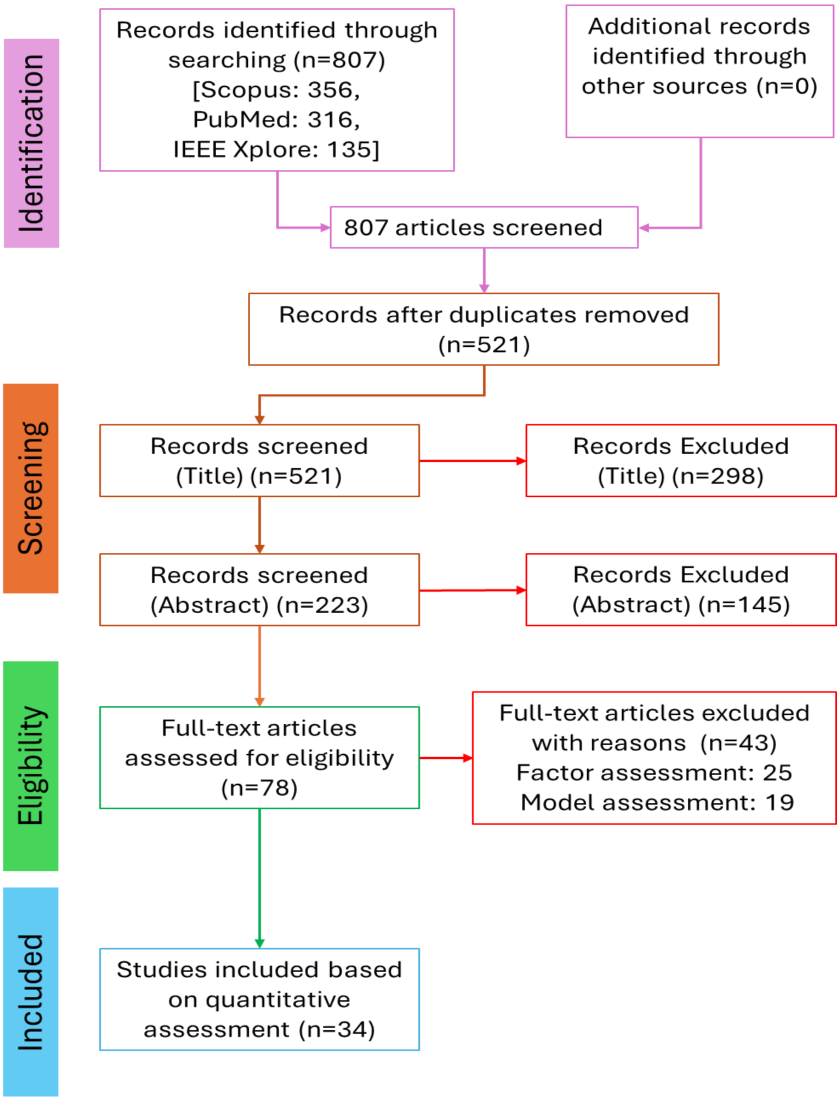

Figure 1: PRISMA Flow Chart Showing The Process Of The Reviewed Studies' Selection At Various Stages

Results

Out of 78 selected articles for full-text assessment, 44 studies were not selected for the following reasons: (a) the studies did not find the PP-related factors (n=25), and (b) the studies did not find the ML-based models (n=19). Finally, 34 studies were selected in this systematic review. Table 3 illustrates the summary of all included articles.

Table 3: Summary Of Included Articles Within The Systematic Review

S. No.	Author	Study Aim	Model	Project Context
1	(Moussa et al., 2024)	The study aims to predict and manage the risk interactions and systemic risks.	DT, RF, ANN, Adaptive boosting regressors (ABR), and Support vector machines (SVM)	Construction
2	(Li et al., 2024b)	The study aims to predict building energy.	Long short-term memory (LSTM), Conditional variational	Energy

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			autoencoder (CVAE), and Domain-adversarial neural network (DANN)	
3	(Andrić et al., 2024)	The study aims to predict the cost of the infrastructure projects.	RF	Construction
4	(Yalçın et al., 2024)	The study aims to predict the cost of construction projects.	Adaptive neuro-fuzzy inference systems (ANFISs), ANN, Gaussian process regression (GPR), LSTM, M5 model trees (M5TREEs), and SVM	Construction
5	(Liben et al., 2024)	The study aims to predict the duration of the construction projects.	ANN, RF, SVM, K-Nearest Neighbors (KNN), and Classification and Regression Trees (CART). and ANN	Construction
6	(Yao & de Soto, 2024)	The study aims to predict the cyber risks in construction projects.	ANN	Construction
7	(Uddin et al., 2024)	The study aims to predict PP using ML.	KNN, LR, SVM, RF, and Boosting	Engineering
8	(Golabchi & Hammad, 2024)	The study aims to predict the utilization of labor resources in construction projects.	Recurrent neural network (RNN)	Construction
9	(Abbasianjahromi & Aghakarimi, 2023)	The study aims to improve project security in the event of incorrect forecasts.	DT and KNN	Construction
10	(Al mnaseer et al., 2023)	The study aims to predict the time and cost overruns of the construction projects.	ANN	Construction
11	(Millán et al., 2023)	The study aims to evaluate and design the standard project engineering management system.	ANN	Engineering
12	(Zhang et al., 2023)	The study aims to predict the funding evaluation decisions based on personal characteristics.	DT	R&D

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13	(Pang et al., 2022)	The study aims to predict the project cost and duration.	LSTM, ANN, Multiple regression (MR), DT, SVM, and RF	IT
14	(Mahmoodzadeh et al., 2022)	The study aims to predict the project cost and duration.	DT, SVM, and GPR	Construction
15	(Taye & Feleke, 2022)	The study aims to predict the failures in project management knowledge areas.	DT, KNN, LR, Naïve Bayes (NB), and SVM	Software
16	(Venkata Ramana & Narsimha, 2022)	The study aims to predict success measures for software project outcomes.	MR	Software
17	(Rathod & Sonawane, 2022)	The study aims to predict project costs and durations using AI.	SVM, ANN, and LR	Construction
18	(Sampaio de Sousa & Villanueva, 2022)	The study aims to predict project revenue.	ANN	Energy
19	(Hanci, 2021)	The study aims to indicate the risk groups for software projects.	NB and DT	Software
20	(Oliveira et al., 2021)	The study aims to minimize the time spent and potential errors during auto-assignment issuance.	NB, KNN, LR, and SVM	Software
21	(Ma et al., 2021)	The study aims to identify the risk factors in construction projects.	Convolutional neural network (CNN), NB, KNN, and SVM	Construction
22	(Gouthaman & Sankaranarayanan, 2021)	The study aims to predict the percentage risk of software models.	KNN, ANN, SVM, and RF	Software
23	(Sousa et al., 2021)	The study aims to determine the risk level associated with project risk factors.	KNN, ANN, RF, NB, and SVM	Software
24	(Bogdan & Marginean, 2020)	The study aims to predict the structure and clarity of software projects.	RF, ANN, and LSTM	Software
25	(Sabahi & Parast, 2020)	The study aims to predict the PP of university undergraduate students.	LR, ANN, SVM, and RF	Academics

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26	(Radliński, 2020)	The study aims to predict customer satisfaction.	KNN, Ensemble approach (EA), SVM, and RF	Software
27	(Yaseen et al., 2020)	The study aims to predict project delays.	RF	Construction
28	(Peña et al., 2019)	The study aims to propose a method for project evaluation.	ANN	Software
29	(Yurdakurban & ErdoĞan, 2018)	The study aims to estimate software effort.	DT, MR, and NB	Software
30	(Pospieszny et al., 2018)	The study aims to estimate the effort and duration of software projects.	SVM and ANN	Software
31	(Wauters & Vanhoucke, 2017)	The study aims to predict future construction project costs.	LR	Construction
32	(Wauters & Vanhoucke, 2016)	The study aims to predict the actual duration of a project.	Bagging, Boosting, SVM, DT, and RF	Construction
33	(Chaudhary et al., 2015)	The study aims to identify the risk factors.	SVM	Software
34	(Han et al., 2015)	The study aims to compare ML algorithms for time prediction.	DT and ANN	Software

To gain a deeper understanding of Table 3, it is essential to examine the results of the RQs.

RQ1: What Are The Research Trends In PP That Use ML-Based Studies?
This systematic review employed descriptive statistics to analyze the findings of the selected studies. The analysis of these studies shows the various trends in the context of PP using ML. Figure 2 shows the year-wise trend. It illustrates that fewer articles were observed in the years 2015 and 2019. The trends increase from 2020 onward in the same research context.

Figure 3 illustrates the purpose of the project-wise trend. This systematic research clustered all the observed study purposes into the following areas: time, cost, operations, resource allocation, quality, safety, customer satisfaction, and risk management. Figure 3 illustrates that time-related factors, along with cost, risk, and quality, are commonly observed in the selected studies. Customer satisfaction and safety-related factors appear only once.

This SLR examined the selected studies that were published between 2015 and 2024. As illustrated in Figure 2, the trend of the research increases over time, starting from 2020 onwards. Various factors likely support this trend. First, advancements in computational power, particularly through the use of cloud computing and GPUs (Silvano et al., 2025). It has made training complicated models more cost-effective and easier. Secondly, this is the era of digitization, in which a large amount of data has been generated during the project process,

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enabling the application of ML (Nishat et al., 2025). Third, the open access of AI tools has made it easier for researchers (Liu, 2025). Ultimately, the COVID-19 pandemic heightened the need for organizations to make data-driven decisions and expedite digital transformation (Amankwah-Amoah et al., 2021). So, these are the facts that transformed the research community into using ML-based approaches to solve PP challenges.

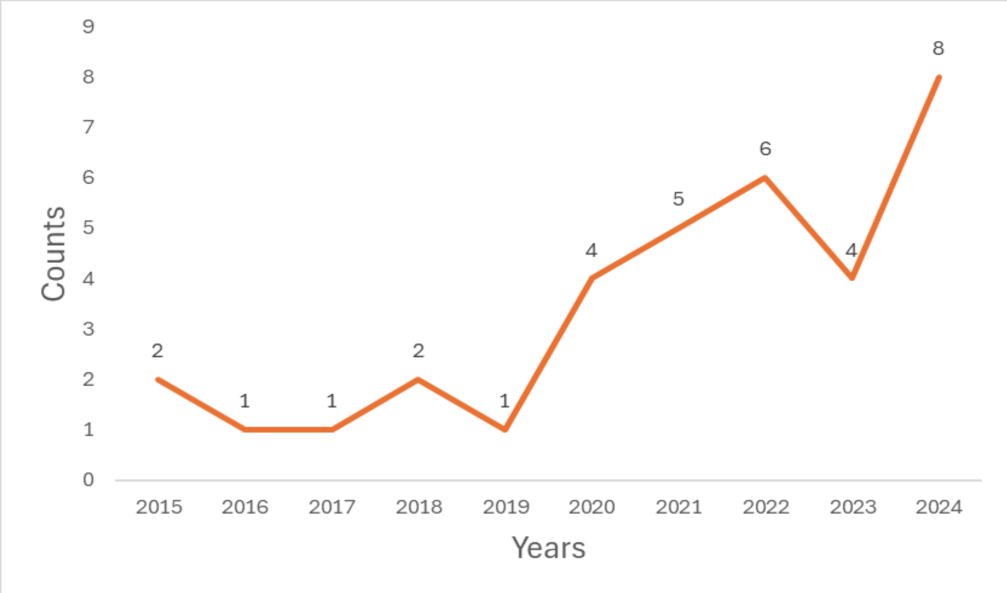

Figure 2: Year-Wise Publication Trend Of Machine Learning Based Studies In The Context Of Project Performance

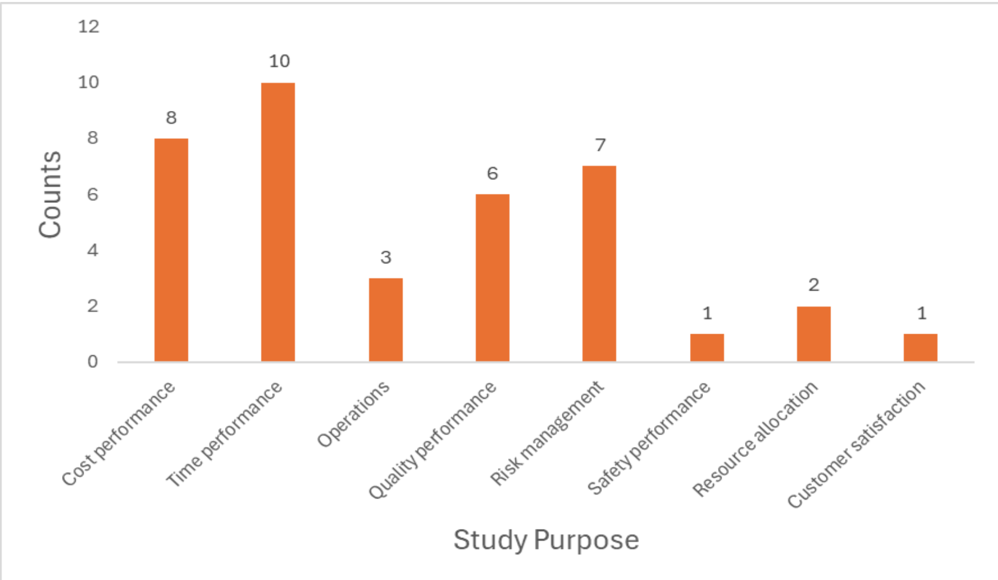

Figure 3: Purpose Of The Study: A Study-Wise Publication Trend Of Machine Learning Based Studies In The Context Of Project Performance

Furthermore, most studies have observed time-related factors. The studies by (Al mnaseer et al., 2023; Han et al., 2015; Liben et al., 2024; Mahmoodzadeh et al., 2022; Oliveira et al., 2021; Pang et al., 2022; Pospieszny et al., 2018; Rathod & Sonawane, 2022; Wauters & Vanhoucke, 2016; Yurdakurban & ErdoĞan, 2018) used the time-related factors; on the other hand the safety-related, and customer-related factors are used in only (Abbasianjahromi & Aghakarimi,

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2023), and (Radliński, 2020) studies respectively. The findings reveal that time-related, risk, cost, and quality factors dominate ML-based PP research because these are the main dimensions of the traditional PP model. These are widely available and well-structured in project-related datasets, and they have a direct influence on decision-making (Kerzner, 2023). On the other hand, safety and customer satisfaction-related factors appear rarely, as they are often industry-specific, inconsistent, and subjective measures. The collection of these factors is also challenging and has some privacy constraints (Martin et al., 2020).

RQ2: Which ML Models Are Most Frequently Applied In PP Studies?
This section provides insights into the most frequently used ML models for PP. Figure 4 illustrates the trend of different ML models used in the reviewed articles of this study. The statistical trend indicates that SVM and ANN are the most commonly used ML models.

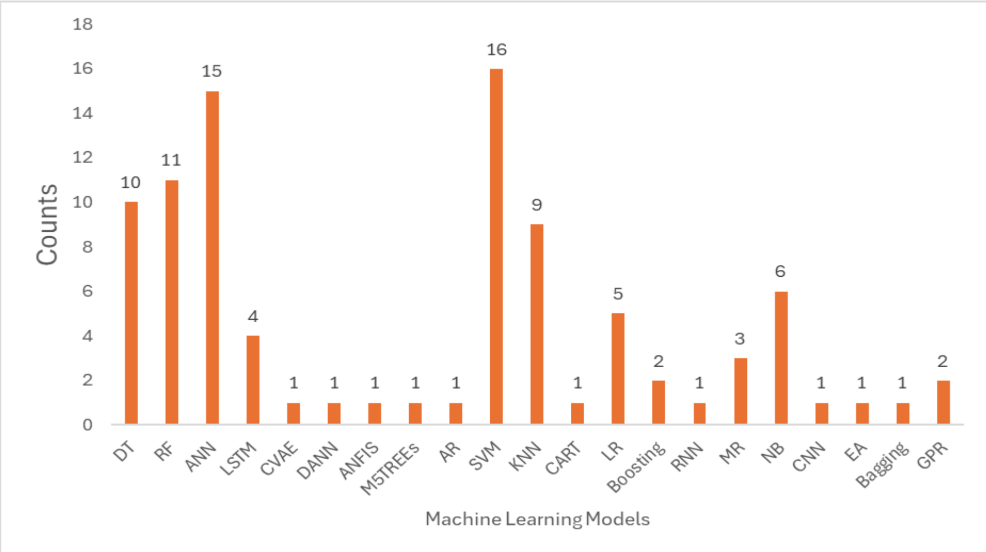

Figure 4: Comparison Trend Of Machine Learning Models In The Context Of Project Performance

This analysis shows that most researchers use the SVM model in the context of PP. The articles (Chaudhary et al., 2015; Gouthaman & Sankaranarayanan, 2021; Ma et al., 2021; Mahmoodzadeh et al., 2022; Moussa et al., 2024; Oliveira et al., 2021; Pang et al., 2022; Pospieszny et al., 2018; Radliński, 2020; Rathod & Sonawane, 2022; Sabahi & Parast, 2020; Sousa et al., 2021; Taye & Feleke, 2022; Uddin et al., 2024; Wauters & Vanhoucke, 2016; Yalçın et al., 2024) used SVM, the articles (Al mnaseer et al., 2023; Bogdan & Marginean, 2020; Gouthaman & Sankaranarayanan, 2021; Han et al., 2015; Millán et al., 2023; Moussa et al., 2024; Pang et al., 2022; Peña et al., 2019; Pospieszny et al., 2018; Rathod & Sonawane, 2022; Sabahi & Parast, 2020; Sampaio de Sousa & Villanueva, 2022; Sousa et al., 2021; Yao & de Soto, 2024; Yalçın et al., 2024) used ANN model, the articles (Andrić et al., 2024; Bogdan & Marginean, 2020; Gouthaman & Sankaranarayanan, 2021; Moussa et al., 2024; Pang et al., 2022; Radliński, 2020; Sabahi & Parast, 2020; Sousa et al., 2021; Uddin et al., 2024; Wauters & Vanhoucke, 2016; Yaseen et al., 2020) used RF model, the articles (Abbasianjahromi & Aghakarimi, 2023; Han et al., 2015; Hanci, 2021; Mahmoodzadeh et al., 2022; Moussa et al., 2024; Pang et al., 2022; Taye & Feleke, 2022; Wauters & Vanhoucke, 2016; Yurdakurban & ErdoĞan, 2018; Zhang et al., 2023) DT model to predict the PP. Moreover, the study (Moussa et al., 2024) used an AR model, the study (Li et al., 2024b) used CVAE and DANN models, the study (Yalçın et al., 2024) used ANFIS and M5TREEs models, the study (Liben et al.,

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2024) used CART model, the study (Golabchi & Hammad, 2024) used RNN model, the study (Ma et al., 2021) used CNN model, the study (Radliński, 2020) used EA model, and the study (Wauters & Vanhoucke, 2016) used Bagging model.

The statistical trends indicate that SVM, ANN, RF, and DT are the most frequently used models, while AR, CVAE, DANN, ANFIS, M5Trees, CART, RNN, CNN, and EA are used only once, making them the least frequently used models in the context of PP. This pattern is due to the specific characteristics of PP datasets, which are typically tabular, and small in size. This type of dataset makes classical ML models, such as ANN, SVM, DT, and RF, more reliable and suitable for prediction problems (Gil et al., 2021). On the other hand, specialized and more advanced ML models, such as CNN, RNN, DANN, and CVAN, require high computational power and a large amount of data for training. Those are not commonly available in the PM context (Uddin et al., 2024). Models such as M5Tress, EA, and ANFIS are considered domain-specific and are rarely applied in PP studies. Therefore, high model complexity, limited dataset sizes, and reduced interpretability are the primary reasons not to use these less common models.

RQ3: In Which Project Contexts Have ML-Based Techniques Been Frequently Used?
This study analyzed how researchers of the selected studies used ML in the context of different projects. Figure 5 shows the project context-wise trend. Most of the selected studies were from the software and construction industries.

This SLR examined the fact that these selected studies (Bogdan & Marginean, 2020; Chaudhary et al., 2015; Gouthaman & Sankaranarayanan, 2021; Han et al., 2015; Hanci, 2021; Oliveira et al., 2021; Peña et al., 2019; Pospieszny et al., 2018; Radliński, 2020; Sousa et al., 2021; Taye & Feleke, 2022; Venkata Ramana & Narsimha, 2022; Yurdakurban & ErdoĞan, 2018) used the ML approach to predict the performance of software projects, and these articles (Abbasianjahromi & Aghakarimi, 2023; Al mnaseer et al., 2023; Andrić et al., 2024; Golabchi & Hammad, 2024; Liben et al., 2024; Ma et al., 2021; Mahmoodzadeh et al., 2022; Moussa et al., 2024; Rathod & Sonawane, 2022; Wauters & Vanhoucke, 2017; Yalçın et al., 2024; Yao & de Soto, 2024; Yaseen et al., 2020) also used ML models in the context of the construction industry. It is also observed that only one study has been conducted that predicts PP in the academic context (Sabahi & Parast, 2020).

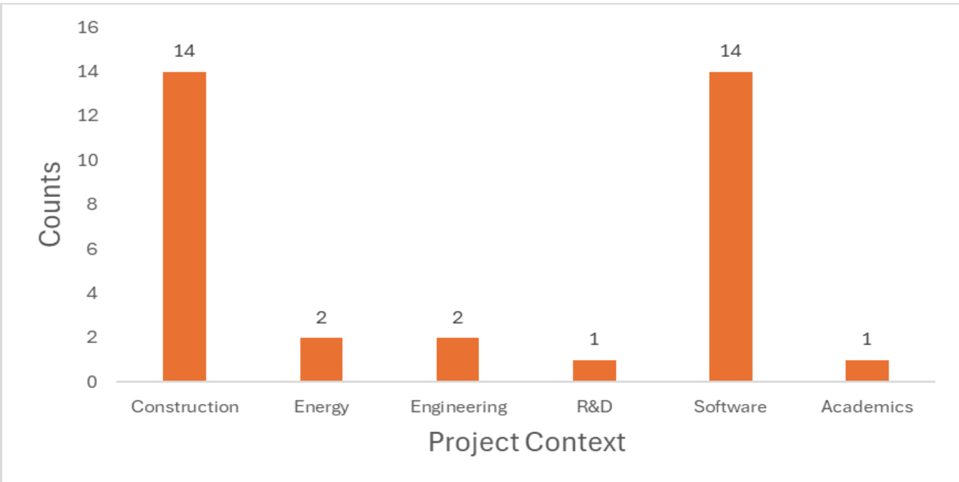

Figure 5: Comparison Trend In The Context Of Different Project Types.

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The results show that ML-based studies are most frequent in the software and construction project contexts, in contrast to academic PP, which remains the least represented. This trend is driven by domain complexity, standardization, and the availability of data. Software projects generate extensive digital traces, including effort metrics, defect logs, and code repositories (Rahman et al., 2024). Similarly, construction projects produce a large amount of heterogeneous and structured data through modern digital technologies such as IoT sensors and building information modeling (BIM). It enables ML models to predict schedule, cost, and risk performance more effectively (Valdebenito & Forcael, 2025). On the other hand, academic PP data are often context-based, fragmented, and less standardized across institutions, which limits the applicability and generalizability of ML applications in an academic context (Ahmed et al., 2025).

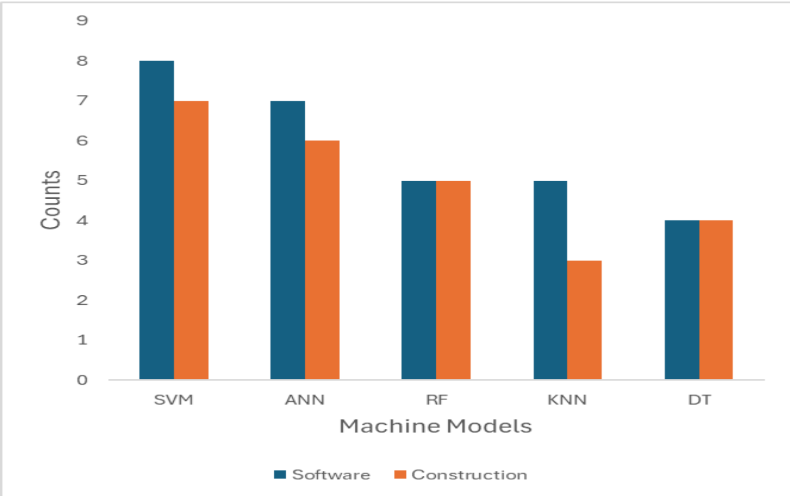

Figure 6: Comparative Distribution Of Dominant Machine Learning Models Across Software And Construction Project Contexts.

Figure 6 shows the relative prominence of common ML models in the construction and software context. SVM and ANN are the most frequently used ML models in the software context that reflect their strong capability and generalization. The survey findings on software engineering support the use of SVM and ANN as the most commonly employed models (Borges, 2020). In construction contexts, both SVM and ANN are shown to be the most common models that maintain their generalization capabilities in the PP domain. RF exhibits balanced usage across contexts, making it consistent with its effectiveness and robustness in handling heterogeneous engineering data. DT and KNN appear not to be commonly used as primary models, suggesting that they are used as baseline models, alongside SVM and ANN. Findings from Fan's (2022) study support this distribution, which emphasizes the effectiveness of margin-based and ensemble models over simpler models for real-world PP predictive tasks.

Discussion

The analysis of ML-based studies in PP reveals a sustained increase in trend since 2020. Certain reasons support this trend. Firstly, the unstructured and structured project data are generated regularly in PM systems due to the digitization of the industrial process. The availability of this massive amount of data necessitates the application of ML models to predict outcomes and extract meaningful insights from the data that were previously difficult to obtain using traditional approaches. This enables researchers to utilize ML applications across various domains (Arrieta et al., 2020). Secondly, the improvement in computational infrastructure

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allows scientists and researchers to train, test, and develop complex ML models through improved scalability and accessibility of computing resources (Sevilla et al., 2022). Moreover, with the passage of time, the maturity of ML models has improved methodologically. Early research articles often used conventional ML algorithms such as DT and regression; conversely, recent studies relied on advanced approaches such as neural networks and ensemble methods. This methodological evolution yields more interpretable, reliable, and factual results, encouraging the broader adoption of ML applications in PP studies (Yu et al., 2023). A recent bibliometric review by Shukery et al. (2025) also supports this increasing trend of ML applications in the PP context.

The analysis also reveals that time-related factors, quality, risk, and cost are the primary considerations in ML-based PP research. At the same time, safety and customer satisfaction are often overlooked. The practical and theoretical reasons support this pattern. First, the importance of quality, cost, and time reflects the influence of the iron triangle. It has a long history of serving as the primary lens for evaluating project success (Atkinson, 1999). These dimensions of the iron triangle are also the most systematic in PM information systems. It produces a massive amount of quantitative and structured data that is suitable for ML applications. Past studies have highlighted that ML adoption in PM is primarily based on consistent and reliable historical data generated from metrics such as quality, cost, risk, and time, rather than qualitative or subjective measures (Uddin et al., 2022). Moreover, industries prioritize these indicators because they indirectly impact project decision-making, prediction, and control (Kerzner, 2023).

In contrast, the customer satisfaction indicator is collected after the project's completion and depends on subjective perceptions across various contexts and stakeholders. These are the reasons that overcome its suitability for ML, which requires large-scale, consistent, and reliable data (Koonsanit & Nishiuchi, 2021). Similarly, the safety data is limited to various industries, such as oil and gas and construction. Organizational privacy concerns, legal restrictions, and confidentiality hinder the availability of safety factor data for academic research (Jang, 2023).

In the context of the most frequently used models, the result section shows that SVM, ANN, and tree-based structures, such as RF and DT, are the most commonly used ML models in the context of PP, reflecting both practical constraints and methodological suitability within the PM domain. These ML models have strong predictive capability, especially when working with project-related datasets that are small in size and well-structured. The stability, reliability, and maturity of these models are highly valued by researchers, particularly in situations where historical data are limited, inconsistent, or sparse (Gil et al., 2021). Moreover, these ML models require less computational power and are easier to implement, making them the best choice even in situations with limited technical capacity. Furthermore, tree-based models such as DT and RF give more precise and meaningful interpretability through decision rules and feature importance. This is particularly important in the context of projects where it is necessary to justify the analytical results at the time of decision-making (Kerzner, 2023).

The less commonly used models in analysis (CVAE, AR, ANFIS, DANN, M5Trees, CNN, RNN, EA, and CART) have limited interpretability, model complexity, and high data requirements. The advanced models, such as CNNs, CVAEs, and RNNs, require high resolution and a massive amount of data, which are commonly not available in PM research. These models demand high computational power, making them less feasible for project contexts (Uddin et al., 2024). Specialized models, such as M5Trees, EA, and ANFIS, are

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primarily adopted in engineering fields. Still, they are not suitable for the PM due to a lack of methodological familiarity in this field. Therefore, the availability of a limited dataset, interpretability demands, the need for transparency in PM environments, and high implementation complexity explain why only classical ML models outperform the current landscape of PP research (Li et al., 2024a).

The concentration of ML-based PP studies in the construction and software industries is due to the high availability of well-structured data and strong commercial incentives to enhance quality, cost, and time-based outcomes. Construction projects increasingly use digital PM tools and sensors that generate a massive amount of data, making the feasibility of applying ML models (Darko et al., 2020). The software industry regularly generates defect, historical effort, and productivity data that are used in training the ML models to predict the PP (Chen et al., 2025). Differences in data structure, problem formulation, and decision-making requirements inherent to each field can primarily explain the dominance of specific ML models across different contexts. In software-related research, the frequent use of SVM and ANN reflects the prevalence of high-dimensional and structured datasets, where complex feature interactions and nonlinear relationships are common. A review study in the software context suggested that SVM and ANN consistently achieve strong performance due to their robustness in handling imbalanced, sparse, and complex feature spaces (Borges, 2020). Meanwhile, in the construction context, the data are often noisy, heterogeneous, and influenced by contextual features such as temporal uncertainty, human factors, and environmental conditions. This characteristic explains the balanced prominence of SVM, ANN, and RF models, which have been recommended in a recent review of construction for their resistance to overfitting and robustness in achieving accurate performance (Zhang et al., 2025). From a theoretical perspective, these trends reinforce the stability of ANN, SVM, and RF as versatile solutions for nonlinear, complex, and real-world scenarios in the generic context of PP prediction. Overall, the observed findings suggest that advances in computational capacity and data availability since 2020 have motivated PM researchers to use the dominant ML models identified in this study for reliable and accurate prediction of PP.

Moreover, the inadequate representation of ML-based PP research in academia, particularly among university students, is alarming. University students will be key contributors to national development and future workforce development (Hameed & Irfan, 2019; Lv et al., 2021). They are not only the innovators of the future but also the backbone of industry performance. Yet, academic projects often lack the longitudinal and well-structured datasets that make them unattractive for advanced ML analysis. Academia focuses more on learning outcomes, skill development, and employability, which are less easily captured in quantitative terms, as compared to industry-driven ML research, which prioritizes efficiency factors such as quality, time, and cost. Project-based learning frameworks developed through industry collaboration have been shown to substantially enhance the future readiness of university students, improving problem-solving competencies, teamwork, and technical skills by up to 25-30% (Naseer et al., 2025). These are essential requirements that industries look for in graduates when hiring new talent. Employers are increasingly demanding adaptability, collaboration, and critical thinking from their employees, rather than merely theoretical knowledge (Li & Jansaeng, 2025). The gap in ML-based PP studies on academic projects, therefore, causes a misalignment of research priorities and a data availability issue. Universities need to generate a massive amount of structured data from student projects to train the ML models accurately. It is vital to develop industry-ready graduates who are capable of minimizing the skills gap, driving future industrial success, and contributing to the nation's economic development.

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Conclusion And Future Research Directions

This systematic research gives a comprehensive and critical understanding of how ML has been used to predict PP across various domains. Ahead of identifying the research trends and frequently used ML techniques, the analysis shows an apparent thematic and methodological convergence in recent research. The increasing trend of using ML approaches for predicting PP since 2020 reflects a broader transition towards data-driven PM, which is enabled by methodological advancements in ML models, improvements in computational infrastructure, and the vast amount of data available due to the industry's digitization. These developments indicate that the prediction of PP based on ML is no longer experimental but is gradually becoming a reliable analytical tool for project contexts.

From a theoretical perspective, this study contributes new knowledge by identifying why specific PP dimensions and ML models dominate the existing literature. The highlighting of cost, quality, time, and risk suggests that current PP research is still primarily focused on efficiency-driven approaches, indicating that it prioritizes objective and quantifiable factors over more subjective dimensions, such as customer satisfaction and safety indicators. This trend emphasizes a theoretical limitation in current ML approaches for PP, which often struggle to capture subjective factors. Methodologically, the dominance of ML models such as SVM, ANN, and RF reflects that these models work well, especially in small datasets, achieving high accuracy with good interpretability. On the other hand, the inadequate use of hybrid and advanced deep learning models suggests that model complexity, the unavailability of a massive amount of data, and concerns about explainability remain substantial barriers to their adoption in the PP context.

The findings of this study have some practical implications for ML professionals and project managers. For professionals, the use of SVM, ANN, and RF models is particularly beneficial in situations where the interpretability of the results is necessary for informed decision-making, and data availability is limited. In such cases, these models provide sufficient and more reliable results with evidence-based guidance for real-world projects. Project managers can use these ML models to monitor deviations in their PP related to risk, schedule, and cost, which may help them develop more informed strategies and implement earlier interventions. At the same time, the lack of focus on customer satisfaction and safety factors underscores the need for industries to enhance ML-driven efficiency metrics with subjective and qualitative-based factors to achieve a more reliable and holistic PP.

The most critical insight of this study is the imbalance in the application context. The application of ML-based PP prediction has been well utilized in the construction and software contexts. In contrast, its applicability in the educational or academic project context is not well explored. This gap is particularly significant given the role of universities and higher education institutions in producing future project professionals. The integration of PP prediction based on an ML framework with an academic environment would improve student skill development and also enhance industry expectations from academic outcomes. This integration would enhance workforce readiness and mitigate skill mismatches in industries, ultimately contributing to improved industrial and economic development.

Several future research directions emerge based on the findings of this systematic review study. First, future studies should focus on the development of ML models that include the underexplored PP factors such as customer satisfaction, safety, and human-based factors. Secondly, future studies should examine explainable ML techniques, such as interpretable ensemble models and hybrid models, to address data scarcity issues in predicting PP. Third, the researchers should investigate ML-based PP prediction in an academic context, with a primary focus on how it enhances the skills of graduates ready to join the industry. Ultimately, future research should shift its focus from algorithm comparison to model deployment challenges, decision impact, and industrial readiness. It bridges the gap between ML research and practical PM implementation.

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