[Journal of International Technology and Information Management](https://scholarworks.lib.csusb.edu/jitim)

Volume 31 | Issue 3 Article 3

2023

The Applications of Artificial Intelligence in Managing Project Processes and Targets: A Systematic Analysis

Cherie Noteboom

Martinson Ofori

Zixing Shen
New Mexico State University, zshen@nmsu.edu

Recommended Citation
Noteboom, Cherie; Ofori, Martinson; and Shen, Zixing (2023) "The Applications of Artificial Intelligence in Managing Project Processes and Targets: A Systematic Analysis," *Journal of International Technology and Information Management*: Vol. 31: Iss. 3, Article 3.
DOI: https://doi.org/10.58729/1941-6679.1558
Available at: https://scholarworks.lib.csusb.edu/jitim/vol31/iss3/3

The Applications of Artificial Intelligence in Managing Project Processes and Targets: A Systematic Analysis

Cover Page Footnote

The three authors contributed equally to this work and are listed alphabetically by their last names.

The Applications of Artificial Intelligence in Managing Project Processes and Targets: A Systematic Analysis

Cherie Noteboom
(*Dakota State University*)

Martinson Ofori
(*Gallup Inc.*)

Zixing Shen
(*New Mexico State University*)
* *The three authors contributed equally, and their names were listed alphabetically.*

ABSTRACT

Artificial intelligence (AI) has emerged as the defining technology of the 21st century and has far-reaching impacts on project management (PM). This study assesses the applications of AI in managing project processes and targets through a systematic analysis of publications from 2017 to 2021. The analysis has revealed interesting insights, trends, gaps, and issues. This study informs the researchers and practitioners of the status of AI applications in the management of project processes and targets. It helps stimulate research efforts that can lead to more advances in applying AI to augment PM practices.

Keywords: artificial intelligence, AI, project management, project processes, project targets

INTRODUCTION

Artificial Intelligence (AI) is the intelligence demonstrated by software, computers, and machines in contrast to the natural intelligence displayed by humans (Kok et al., 2009). It has gained fresh momentum with remarkable breakthroughs in the past decade (Davenport, 2018). The recent AI renaissance has been driven by technological advances in information processing and data storage as well as the increasing availability of big data (Pan, 2016). With the promise to maximize the chance of achieving the goals by acting based on data collected from the environment, AI can change how people interact with their gadgets and systems in their everyday life and how businesses manufacture goods and provide services (Makridakis, 2017). AI can transform every industry and discipline (Canhoto & Clear, 2020), including Project Management (PM) (Ong & Uddin, 2020).

This paper uses AI as an umbrella term for any computer program that can perform tasks characteristic of human intelligence. From SIRI to self-driving cars, AI has become increasingly sophisticated. AI technologies, such as machine learning (ML), deep learning (DL), and natural language process (NLP), can now recognize patterns more quickly and with less human coaching (and, eventually, perhaps no coaching). They can make more accurate data-driven decisions and solve business problems using new unstructured data sources, including images, sound, videos, texts, and mapping data. AI applications have been developed and deployed rapidly. They are now found in business functions like finance, marketing and sales, human resources, customer services, and operations in various industries, including banking, manufacturing, and retailing (Halper, 2017). They show great promise and create incredible opportunities to improve efficiency and increase productivity (Makridakis, 2017; Schoper et al., 2018).

Projects are temporary endeavors to create a unique product, service, or result (Project Management Institute, 2017). They are the building blocks of contemporary organizations. Most projects are complex and multi-faceted and require careful management. PM is the application of knowledge, skills, tools, and techniques to project activities to meet the project requirements (Project Management Institute, 2017). PM involves various people (e.g., PM manager, team members, and external stakeholders), different processes (e.g., initiating, planning, and executing), numerous knowledge areas (e.g., integration, quality, and risk), myriad techniques (e.g., Gantt chart, PERT (Program Evaluation and Review Technique), and multiple constraints (e.g., cost, time, and scope) (Heagney, 2016). PM is essential for project success (Munns & Bjeirmi, 1996). In today's rapidly changing business environment, PM enables organizations to succeed in projects challenged with tighter budgets, shorter timelines, and limited resources.

AI can profoundly impact many aspects of PM (Auth et al., 2021; Dam et al., 2019; Uchihira et al., 2020). For example, AI-based tools can take over functions like meeting planning, reminders, day-to-day updates, and other administrative tasks. More importantly, they can help project managers and team members with higher-lever, complex data-driven decision-making, such as complexity and success analyses and risk assessments, to keep projects on schedule and budget. Moreover, AI applications can do more than estimate costs and schedules. They can also analyze data from current and previous projects to provide insights, steering projects through difficult decisions and unexpected obstacles. In short, AI applications are emerging to evaluate, analyze, or forecast potential outcomes based on possible variations of the project or environmental variables and their relationships with other variables.

.

Both PM academia and professionals recognize AI's potential impacts, increasingly interested in integrating AI into PM. A growing number of research has been paying attention to using AI in PM. Most existing research has focused on either developing an AI solution for a specific PM task (e.g., Dam et al., 2019) or discussing the promises and challenges of AI for PM conceptually (Auth et al., 2021). Although these studies have provided interesting insights, they have not synthesized the literature on the actual AI applications in PM. As a result, a comprehensive review of the AI applications in real-world PM settings has been lacking. Subsequently, how different AI technologies are used for PM is unclear. A thorough understanding of the real AI applications in PM is needed to comprehend the current state and guide future research.

This study answers this call. Specifically, we conduct a systematic review of how AI technologies are applied in the PM domain. Of the many aspects of PM, we look into project processes and targets. We chose to study project processes because PM is accomplished through applying and integrating project processes (Project Management Institute, 2017). The PMBOK® Guide defines five PM processes initiating, planning, executing, monitoring and controlling, and closing (Project Management Institute, 2017). The initiating process involves starting up a new project. Within the initiation phase, the business problem or opportunity is identified, a solution is defined, a project is formed, and a project team is appointed to build and deliver the solution. The planning process ensures that the project plans are documented, the project deliverables and requirements are defined, and the project schedule is created. It involves establishing the scope, refining the objectives, and defining the course of action. The executing process is about implementing all the activities set in the planning process to deliver the expected results. The monitoring and controlling process involves actively reviewing the project's status as it proceeds, regulating the performance and progress, evaluating potential obstacles, and implementing necessary changes. The closing process is the final phase of the project lifecycle, where all deliverables are finalized and formally transferred, and all documentation is signed off, approved, and archived.

Project targets refer to a set of fixed goals that determine how a given project is expected to be done and what result or effect is supposed to be produced by the project. They are critical to PM as they provide goals for the project team. Ideally, a project should have definite starting and ending points time, a budget, a clearly defined scope or magnitude of work to be done, and specific performance requirements that must be met. Therefore, the four primary targets are time, scope, cost, and performance (Heagney, 2016). The time target is related to the project's schedule for completion, including the deadlines for each phase of the project and the date for the rollout of the final deliverable.

The scope target defines the project's specific goals, deliverables, features, and functions, in addition to the tasks required to complete the project. The cost target,

.

often dubbed the project's budget, comprises all the financial resources needed to complete the project on time and in its predetermined scope. The performance target concerns whether project deliverables satisfy the needs and expectations of the project's end-user. With a defined target, it is easier for the project manager and team members to focus on reaching it.

Our review makes research and practical contributions to the PM field. It informs PM researchers and practitioners of the status of documented real-world AI applications in PM. Our findings can stimulate interest in adopting AI in PM practices and invite more research efforts that can lead to more advances in applying AI to PM. The remainder of the paper is organized as follows. The next session describes the review method, detailing the sampling and coding processes. Thereafter, the review results are presented. This is followed by discussions of review findings, research agenda, practical significance, and limitations.

The last section concludes the paper.

METHODS

Search Strategy and Selection Process

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) model was followed in searching the literature and selecting papers (See Figure 1). Initially developed for the health sciences, the PRISMA model is an evidence-based minimum set of items for reporting in systematic reviews and meta-analyses (Liberati et al., 2009). Over the years, the PRISMA model has been expanded to many other disciplines, including business and technology (e.g., Peixoto et al., 2021; Regona et al., 2022). It can help our review to synthesize the state of knowledge in the AI application in PM and identify future research priorities. It also provides transparency in the review process and supports duplication of the review. Therefore, the PRISMA model is appropriate for our systematic literature review.

First, four databases (i.e., ABI/Inform, ACM, IEEE Xplore, and Pubmed/Medline) were queried with two keywords – artificial intelligence (AI) and project management (PM), for research published in a 5-year time reference period (2017-2021). The keyword search generated 617 papers. After duplicated papers were removed, 613 unique pieces remained. Next, the abstract of the 613 papers was checked. A reading of the abstract indicated that five hundred twenty-six papers were unrelated to applying AI in the PM domain (e.g., Do et al., 2019) and thus was removed for further analysis.

Then the full text of the remaining 87 papers was examined.

.

The following categories of articles were excluded: (1) full text was not available (e.g., William et al., 2021), (2) research was not empirical but conceptual such as literature review (e.g., Ahmed & El-Sayegh, 2020), (3) AI application was not directly linked to PM (e.g., Fridgeirsson et al., 2021), and (4) AI application was lacking in PM (e.g., Yang, 2021). Finally, 52 papers (indicated with * in the reference section) with AI applications specific to PM were selected for further analysis. Specifically, we analyzed their abstracts and coded them.

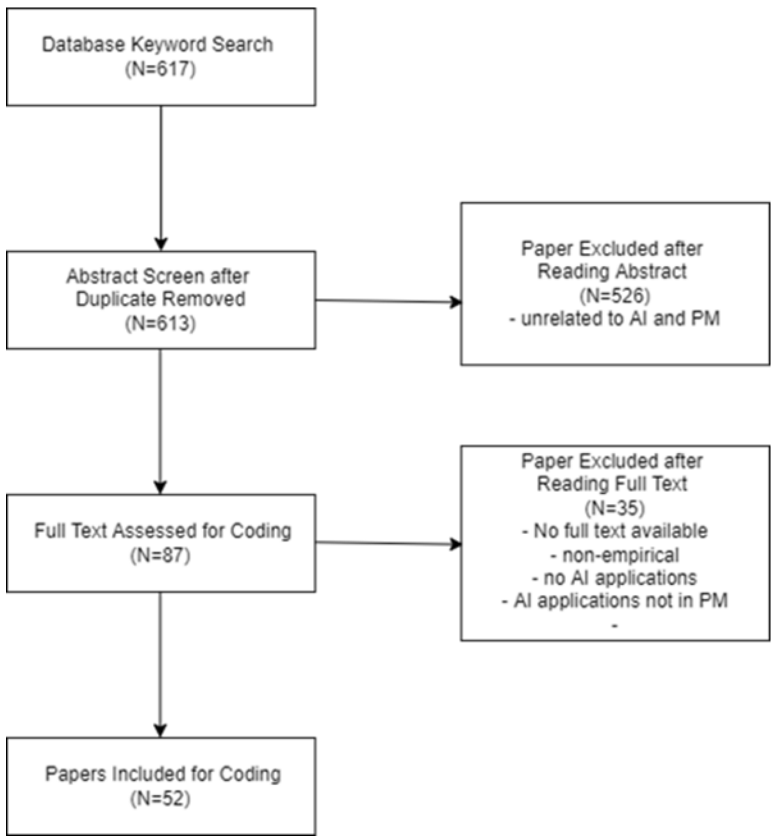

Figure 1. PRISMA Flow Diagram

.

Abstract Analysis

We conducted a word cloud analysis to have a quick and easy understanding of the topical content of sampled papers. Word clouds are graphical representations of word frequency that give greater prominence to words that appear more frequently in a source text (Lee 2020). It can help identify the most salient themes and convey crucial information in textual data. The more often a specific word appears in a source of textual data (such as a speech or database), the more important it is, and the bigger and bolder it appears in the word cloud. A variety of word cloud generators are freely available on the internet. We used the word cloud generator from WordClouds.com. We imported the abstract from the 52 sampled papers into a text box, and the tool created a graphical representation of the words.

Coding Procedure

A coding sheet was first developed. Special attention was paid to AI research areas and techniques, data sources and size, PM processes and targets, and publication outlet and year. AI is a vibrant field with various technical areas across different methods and applications. We adopted the AI framework proposed by Kroenke & Boyle (2021) to guide our coding of AI. As shown in Figure 2, AI research areas include NLP, computer vision, ML, robotics, knowledge representation, and AI planning. NLP strives to give computers the ability to analyze, understand and respond, ultimately making computers interface with human languages rather than computer languages (Shen, 2020). Computer vision enables computers to derive meaningful information from digital images, videos, and other visual inputs and take actions or make recommendations based on that information (Szeliski, 2022). ML focuses on the idea that computers can identify patterns and make decisions from data with minimal human intervention (Louridas & Ebert, 2016). Robotics is interested in designing, constructing, and using machines (robots) to perform tasks traditionally done by humans (Murphy, 2019). Knowledge representation represents information computers can understand and utilize to solve complex real-world problems (Bench-Capon, 2014). AI planning concerns how computers execute strategies or action sequences with autonomous techniques for complex problems (Hendler et al., 1990). These AI areas are not mutually exclusive but somewhat intertwined. For example, ML has been widely used in other AI areas, such as NLP and AI planning. AI techniques include but are not limited to, random forests regression, support vector machine, genetic algorithm, linear regression, naive Bayes, and convolution neural network.

.

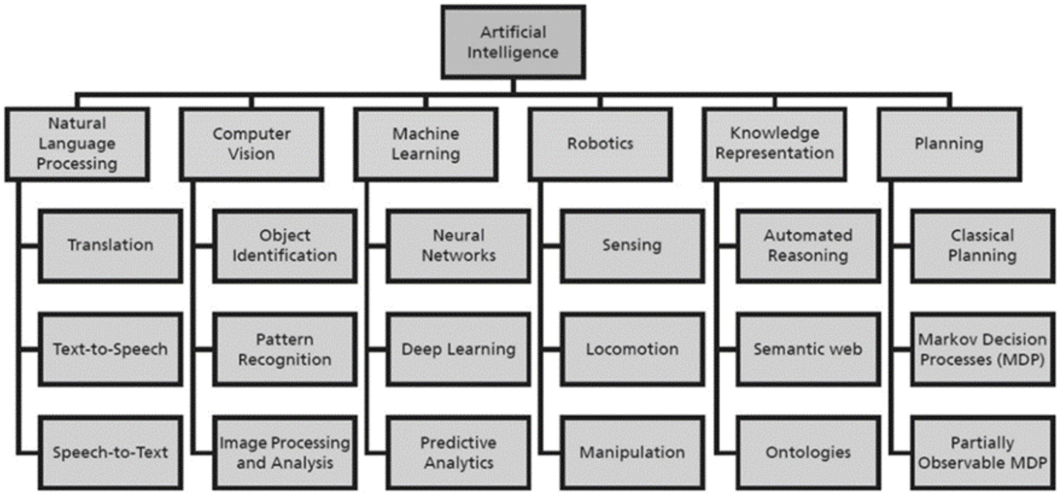

Figure 2. Major AI Research Areas (adopted from Kroenke & Boyle, 2021)

AI applications rely on enormous amounts of data from which to observe trends and behavior patterns and quickly adapt to improve the accuracy of the conclusions derived from the analysis of those data (Aerts & Bogdan-Martin, 2021).

Such applications do not just require more information than humans to understand concepts or recognize features; instead, they require hundreds of thousands of times more. In addition to quantity, data quality is essential to AI applications (Bertossi & Geerts, 2020). The outcomes of AI applications are only as good as the data that humans feed them to learn. Quality data in large volumes are needed for AL to make accurate predictions. Considering the criticality of data to AI applications, we also collected information on the data used in the AI application, including data source and data size.

Next, the PM processes, initiating (defining or initiating a project or phase), planning (establishing the scope, refining the objectives, and defining the course of action), executing (completing the work described in the project plan), monitoring & controlling (tracking, reviewing and regulating the performance and progress) and closing (processes to formally complete and close), were coded. The PM targets (time, cost, scope, and performance) were also coded for each AI application.

Time refers to the schedule for the project to reach completion. Cost is the financial constraint of a project, also known as the project budget. Scope is the "size" of the project in terms of the details and magnitude of the project's deliverables. Performance is concerned with the overall measurement of whether a project has met the objectives and requirements.

.

Finally, the industry to which AI was applied was noted. We also checked the publication outlet and year for the sampled research. Each paper was read and analyzed using the coding sheet. Table 1 shows an example of the coding of a paper. The summary of the coding of 52 papers is listed in Appendix.

Table 1. Example of Coding Sheet

Paper: Suherman and colleagues, 2020	
AI research area	ML
AI technique	random forests regression
Data source	COCOMO NASA93 that available publicly on the internet
Data Size	not reported
PM process	Planning
PM Target	Effort estimation – scope
Industry	Software
Publication outlet	Conference
Publication year	2020

RESULTS

Abstract Summary

The word cloud generated from the abstracts of all 52 selected studies is shown in Figure 3. It reveals that the development of AI algorithms and models is dominant, and software, construction, and energy projects are frequent in the sampled papers. It also shows that the important words for PM include prediction accuracy, project defect prediction, software effort estimation, project resources conflict, software requirement specifications, risk value, and risk factor. The most often cited AI-related terms encompass ML, neural networks, genetic algorithms, random forests regression, decision trees, and supervised learners.

.

Figure 3. Word Cloud based on Abstracts

AI Research Areas and Techniques

Although AI has evolved in various research areas over the years, AI applications of computer vision, robotics, knowledge representation, and AI planning were not found in the selected studies. Most sampled papers involved mostly ML (78.85%, n=41), while the remaining were NLP (21.15%, n=11). We also observed that ML was utilized in all the papers focused on NLP. All 52 sampled studies employed supervised ML. ML functions on supervised and unsupervised algorithms.
The key difference between the two algorithms lies in the data fed into the algorithm. Supervised ML uses input data already tagged with the correct answer and produces output data from previous experiences. Unsupervised ML allows acting upon input data, which are neither classified nor labeled, to unknown patterns in data without human supervision.

Table 2. AI Techniques

AI Techniques	N	%
Neural Network	**22**	**42.31%**
Artificial Neural Networks	7	13.46%
Deep Neural Networks	7	13.46%
Recurrent Neural Networks	6	11.54%
Convolution Neural Networks	1	1.92%
Extreme Learning Machine	1	1.92%
Ensemble	**18**	**34.62%**
Random Forests	10	19.23%

.

Decision Trees	3	5.77%
XGBoost	3	5.77%
Gradient Boosting	1	1.92%
M5P Regressor	1	1.92%
Optimization	**10**	**19.23%**
Genetic Algorithm	4	7.69%
Gradient Descent Optimization	3	5.77%
Bilevel Optimization	1	1.92%
Particle Swam Optimization	1	1.92%
MaxLogit Algorithm	1	1.92%
Support Vector Machines	**7**	**13.46%**
Support Vector Classification	5	9.62%
Support Vector Regression	2	3.85%
Linear Model	**7**	**13.46%**
Logistic Regression	4	7.69%
Linear Regression	2	3.85%
Ridge Regression	1	1.92%
Others	**13**	**9.62%**
Naive Bayes	4	7.69%
k-Nearest Neighbor	2	3.85%
Statistical Learning	1	1.92%
Fuzzy Logic	1	1.92%
Random Space Classical Analogy	1	1.92%
Simulated Annealing	1	1.92%
Classical Analogy	1	1.92%
Case-based Reasoning	1	1.92%
Discriminant Analysis	1	1.92%

The most popular techniques used in the sampled research include neural networks, ensemble methods, support vector machines, and linear models, as shown in Table 2. Some papers utilized multiple AI techniques (e.g., Ali et al., 2021; Oliveira et al., 2021; Shrikanth et al., 2021; Choi et al., 2021). Findings on each of the popular AI techniques are presented below.

.

Neural Network

In AI, a neural network is a method that teaches computers to process data in a way that mimics the human brain through a set of algorithms. It has gained traction in research and real-world projects across various domains to achieve high predictive power. Twenty-two of the selected articles (42.31%) used some form of the neural network, like an artificial neural network (e.g., Bai et al., 2021; Desai & Mohanty, 2018; Ranković et al., 2021), deep neural network (e.g., Khan et al., 2021; Tamura & Yamada, 2017), recurrent neural network (e.g., Chatterjee et al., 2020; Predescu et al., 2019), convolution neural network (Zhong et al., 2021) and extreme learning machine (De Carvalho et al., 2021).

Ensemble

The ensemble method combines several base models to create better predictive models than could be obtained from any constituent models alone. Eighteen sampled papers (34.62%) utilized the ensemble method, including random forests (e.g., Osman & Zaharin, 2018; Owolabi et al., 2020), decision trees (e.g., Ali et al., 2021; Shrikanth et al., 2021), XGBoost (e.g., Eken et al., 2019; Elmousalami, 2021), gradient boosting (Choi et al., 2021) and M5P Regressor (Dritsas et al., 2021).

Support Vector Machine

A support vector machine (SVM) uses classification algorithms for two-group classification problems. An SVM model can categorize new text when given a set of labeled training data per category. SVM models perform well with a limited amount of data to analyze. They are suitable for predicting either discrete labels or continuous values. Seven of the selected articles (13.46%) employed the SVM technique for classification tasks (e.g., Hammad & Alqaddoumi, 2018; Pohl et al., 2020) and regression tasks (Lin et al., 2019; Lopez-Martin et al., 2017).

Linear Model

Linear models predict continuous numerical values using a linear function of the input features. They make predictions of a dependent variable value from a given independent variable based on supervised learning. Seven papers (13.46%) employed linear models, such as linear regression (Arage & Dharwadkar, 2017; Hanslo & Tanner, 2020), logistic regression (e.g., Assavakamhaenghan et al., 2020; Oliveira et al., 2021), and ridge regression (Ali et al., 2021).

.

Optimization

Optimization is the process where the model is trained iteratively to create an accurate model with less error rate. In the optimization process, the hyperparameters are tuned until the optimum result is reached. Ten papers (19.23%) used optimization models such as genetic algorithms (Kareem Kamoona & Budayan, 2019; Ma & Deng, 2021), gradient descent optimization (e.g., Oliveira et al., 2021; Zhang & Wang, 2021), bilevel optimization (K. Li et al., 2020), particle swam optimization (Lin et al., 2019), the maxlogit algorithm (Assavakamhaenghan et al., 2020).

Others

As expected, the list above is not exhaustive. Several other categories of ML algorithms were applied in the sampled literature. They were k-nearest neighbors (Korenaga et al., 2019), naïve Bayes (Eken et al., 2019), fuzzy logic (Peña et al., 2019), simulated annealing (Lu et al., 2017), classical analogy (Hosni & Idri, 2017), statistical learning (Zhang & Wang, 2021), random space classical analogy (Hosni & Idri, 2017), case-based reasoning (Asif & Ahmed, 2020), and discriminant analysis (Masuda et al., 2017).

DATA SOURCE AND SIZE

Data were acquired from various sources. These different data sources can be grouped into publicly available and institutional proprietary, as shown in Table 3. Examples of publicly available data sources include Desharnais Software Cost Estimation (n=5) (e.g., Ali et al., 2021; De Carvalho et al., 2021), Constructive Cost Model (COCOMO) (n = 4) (e.g., Hosni & Idri, 2017; Khan et al., 2021), and the NASA dataset (n =4) (e.g., BaniMustafa, 2018; Suherman et al., 2020). Institutional/proprietary data were from software requirements specification (SRS) documents (e.g., Anish et al., 2019; Chatterjee et al., 2020) and construction projects (e.g., Lin et al., 2019; Yaseen et al., 2020). Some papers did not report their data source (e.g., Lu et al., 2017; Ma & Deng, 2021). Proprietary data were utilized more frequently than publicly available data. Data size also ranged from 4 SRS documents (Osman & Zaharin, 2018) to 80,000 JIRA issues (Assavakamhaenghan et al., 2020). Given the difference in the unit of analysis for each, the data sizes were not categorized but have been listed in the Appendix.

.

Table 3. Data source

Data Source	N	%
Instuitional Proprietary	34	30.77%
Publicly available	16	65.38%
Not Reported	2	3.85%

PM Process

Table 4 provides an overview of the PM processes covered by the selected papers. No study applied AI to the closing process. Next, we detail the findings on the initiating, planning, executing and monitoring, and controlling processes.

Table 4. PM Process

PM Process	N	%
Initiating	**14**	**26.92%**
Cost prediction	7	13.46%
Risk prediction	4	7.69%
Schedule management	3	5.77%
Planning	**21**	**40.38%**
Effort estimation	13	25.00%
Human resource management	3	5.77%
Requirements management	3	5.77%
Team formation	1	1.92%
Scrum adoption prediction	1	1.92%
Executing	**7**	**13.46%**
Effort estimation	3	5.77%
Communication management	1	1.92%
Technical Debt prediction	1	1.92%
Execution control	1	1.92%
Risk prediction	1	1.92%
Monitoring & Controlling	**10**	**19.23**
Defect prediction	7	13.46%
Performance evaluation	1	1.92%
Scrum adoption prediction	1	1.92%
Maturity prediction	1	1.92%

.

Initiating

Fourteen (26.92%) papers dealt with the initiating process. Seven studies developed AI applications to answer the question “What is the estimated cost of the project?” (Arage & Dharwadkar, 2017; Desai & Mohanty, 2018; Elmousalami, 2021; García Rodríguez et al., 2019; Kareem Kamoona & Budayan, 2019; Lin et al., 2019; Choi et al., 2021). Four articles explored risk prediction to generate a broad perspective of the opportunities and threats to the project (Ajayi et al., 2020; Asif & Ahmed, 2020; Owolabi et al., 2020; Zhong et al., 2021). Further, three articles dealt with schedule information management aimed at approximating the completion time for the project (Lu et al., 2017; Ma & Deng, 2021; Zhang & Wang, 2021).

Planning

Twenty-one papers (40.38%) were related to the planning process. They were all about software-based project planning. A large majority (n=13) experimented with software effort estimation (Ali et al., 2021; BaniMustafa, 2018; Choetkiertikul et al., 2019; De Carvalho et al., 2021; Hammad & Alqaddoumi, 2018; Hosni & Idri, 2017; Ionescu, 2017; Khan et al., 2021; Korenaga et al., 2019; Predescu et al., 2019; Ranković et al., 2021; Suherman et al., 2020; Tamura et al., 2018). The remaining eight articles focused on how to plan for project scope, with three on human resource management (Assavakamhaenghan et al., 2020; Bai et al., 2021; Dritsas et al., 2021), three on function management (Anish et al., 2019; Chatterjee et al., 2020; Osman & Zaharin, 2018), and one each on critical success factors (Perera et al., 2021) and (Masuda et al., 2017).

Executing

Seven publications (13.46%) looked into the executing process. They covered AI-enabled tools to improve the software development process (Lopez-Martin et al., 2017; Mahfoodh & Hammad, 2020; Oliveira et al., 2021), predict software development technical debt (Wang et al., 2020), support project execution control (Peña et al., 2019), enhance effective team collaboration (Buah et al., 2020), and predict project execution delay (Yaseen et al., 2020)

Monitoring and Controlling

Ten articles (19.23%) focused on the monitoring and controlling process. Some studies designed AI applications to detect, track or predict software bugs and defects

.

(Eken et al., 2019; K. Li et al., 2020; Y. Li et al., 2017; Mahfoodh & Obediat, 2020; Pohl et al., 2020; Shrikanth et al., 2021; Tamura & Yamada, 2017). Others focused on performance evaluation (Li, 2021), scrum adoption prediction (Hanslo & Tanner, 2020), and maturity prediction (Liu et al., 2017).

PM TARGET

Listed in Table 5 is the information regarding PM targets in the sampled papers. These targets were organized according to the triple constraint of project management.

Table 5. PM Target

PM Target	N	%
Time	**4**	**7.69**
Schedule management	3	5.77%
Technical debt prediction	1	1.92%
Cost	**7**	**13.46**
Cost prediction	7	13.46
Scope	**30**	**57.69%**
Effort estimation	16	30.77
Risk prediction	5	9.62
Requirement management	3	5.77
Human resource management	2	3.85
Risk management	1	1.92
Team formation	1	1.92
Critical Success Factors	1	1.92
Communication management	1	1.92
Performance	**11**	**21.15**
Defect prediction	7	13.46%
Performance evaluation	1	1.92%
Scrum adoption prediction	1	1.92%
Execution control	1	1.92%
Maturity prediction	1	1.92%

.

Time

Every project is a limited-time endeavor. This means time is an essential resource to the project, which can contribute to the success or failure of the project. Four papers (7.69%) explored the time constraint of PM, specifically schedule management (Lu et al., 2017; Ma & Deng, 2021; Wang et al., 2020) and technical debt prediction (Zhang & Wang, 2021)

Scope

The scope of the project is also essential for defining the entire project. It determines the size of the project about detail, quality, and the scale of the project deliverables. More than half of the studies surveyed – thirty (57.69%) – dealt with issues concerning this constraint. Sixteen papers examined effort estimation (e.g., Choetkiertikul et al., 2019, 2019; Ionescu, 2017), five explored risk prediction (e.g., Owolabi et al., 2020; Yaseen et al., 2020), three were on requirements management (Anish et al., 2019; Chatterjee et al., 2020; Osman & Zaharin, 2018), and two on human resource management (Assavakamhaenghan et al., 2020; Dritsas et al., 2021). The remaining were risk management (Bai et al., 2021), team formation (Masuda et al., 2017), critical success factors (Perera et al., 2021), and communication management (Buah et al., 2020).

Cost

A project's budget allows it to be completed on time and within the specified scope. Thus, the cost of a project is also critical to its success. Overall, seven (13.46%) of the studies in this literature review were found to explore topics about the cost of the project (e.g., Elmousalami, 2021; Kareem Kamoona & Budayan, 2019; Lin et al., 2019).

Performance

Eleven (21.15%) of the surveyed studies explored topics regarding project performance. These included seven on defect prediction (e.g., Pohl et al., 2020; Tamura et al., 2018). Others were scrum adoption prediction (Hanslo & Tanner, 2020), performance evaluation (H. Li, 2021), maturity prediction (Liu et al., 2017), and execution control (Peña et al., 2019).

.

INDUSTRY

Summarized in Table 6 is the distribution of industry. The IT/Software industry was predominant, with 37 papers (71.15%) applying AI to bug tracking, defect prediction, and effort estimation problems. This was followed by the Construction and Energy industries with eight (15.38%) and two (3.85%) papers, respectively. One paper surveyed project managers but was not industry-specific (Bai et al., 2021). With only one article each, other industries included procurement (García Rodríguez et al., 2019), transportation/logistics (H. Li, 2021), human resource management (Dritsas et al., 2021), and farming and agriculture (Elmousalami, 2021). The dominance of IT/software development projects in the sampled papers can be attributed to at least two factors. First, project teams working on IT/software development are knowledgeable of AI technologies and techniques and are comfortable applying them to PM. Second, AI techniques are readily applicable to many repetitive tasks in software development, such as cost, debugging, and testing.

Table 6. Industry Distribution

Industry	N	%
IT/Software Development	**37**	**71.15%**
Construction	**8**	**15.38%**
Energy	**2**	**3.85%**
Others	**5**	**7.70%**
- Procurement	1	1.92%
- Transportation & Logistics	1	1.92%
- Human resource management	1	1.92%
- Farming/Agriculture	1	1.92%
Not mentioned	**1**	**1.92%**

PUBLICATION STATISTICS

Table 7 shows the information on publication outlets and years. Of the 52 selected studies, 30 of the articles (57.69%) were in the proceedings of conferences like the IEEE/ACM International Conference on Automated Software Engineering (ASE) and the International Conference on Reliability, Infocom Technologies, and Optimization (ICRITO). The remaining 22 papers (42.31%) were published in international English-language journals such as IEEE Access (n=5), Sustainability (n=3), and Mathematical Problems in Engineering (n=3).

.

Most selected papers were published in 2021, and 29 were published in the last two years (55.77%). Publications have been growing steadily in the last three years. Next, we report the review findings on AI, PM, and industry.

Table 7. Publication Outlet and Year

Publication Outlet	N	%
Conference Proceedings	30	57.69
Journal articles	22	42.31
Publication Year	**N**	**%**
2017	9	17.31%
2018	5	9.62%
2019	9	17.31%
2020	14	26.92%
2021	15	28.85%

DISCUSSION

Summary of Results

In our review, over 600 records were narrowed down to 52 full-text articles. The analyses of the 52 papers have revealed some interesting patterns in the applications of AI in PM, such as the popularity of ML (especially supervised ML), the limited availability of data, wide use of AI in IT/software development projects. More importantly, our review provides empirical evidence that AI applications play significant roles, from conceptualizing and planning to implementing, monitoring, and evaluating projects. AI is shown to effectively manage the time, scope, and cost targets at the different PM processes, contributing to the projects' performance.

In construction projects, AI has been applied to predict various PM targets. Yaseen and colleagues (2020) developed an AI model called integrative random forest classifier with genetic algorithm optimization to predict delay (missing the deadline). Based on the measured accuracy, kappa statistics, and classification error, the model was robust and reliable to predict project delay (time target) in the executing process. Owolabi and colleagues (2020) also took an interest in project delay, specifically in public-private partnerships construction projects. They devised a series of predictive models using linear regression, regression trees, random forest, support vector machine, and deep neural network to predict construction project completion. Their study found that random forest is an effective technique for predicting delays with lower average test predicting error

.

than other techniques. Zhang and Wang (2021) examined another aspect of the time target – schedule management – in the initiating process. Their ML-based model was demonstrated to estimate task duration with improved computation efficiency without losing any prediction accuracy.

Arage and Dharwadkar (2017) forecast the cost of construction projects based on district schedule rates in the initiating process with a simple linear regression model. The proposed model, tested with a small dataset, gave 91% to 97% prediction accuracy. More sophisticated models are also developed to estimate construction costs to provide a reliable basis for decision-making at the onset of projects. Lin et al. (2019) proposed a support vector machine model optimized by a particle swarm optimization algorithm with principal component analysis for power substation projects. The model was shown to have lower error rates and higher prediction accuracy than traditional models.

Moreover, AI applications find ways to predict risks associated with more than one PM target. For instance, Zhong and colleagues (2021) proposed an AI model based on the one-dimensional convolution neural network to forecast risks associated with time and cost. After training and learning, the model could predict construction period risk and cost risk with an average absolute error of less than 0.1%. This shows AI-based model can solve the problem of low accuracy of traditional construction project time and cost prediction in the planning process. Choi et al. (2021) developed an AI-based intelligent decision support system with different modules for cost estimation in the initiating process, schedule delay in the executing process and maintenance prediction in the monitoring and controlling process. The system can help project managers with risk management by preventing errors and improving work accuracy.

Similarly, AI shows promise in the different PM processes in software projects. Four papers examined AI applications in the initiating process. Two of them focused on schedule management. Ma and Deng (2021) used use genetic algorithm to solve the problems in project scheduling. They showed that AI could find the optimal schedule plan by satisfying the project priority and resource constraints for medium or large-scale software projects. Lu and colleagues (2017) designed a hybrid algorithm combining simulated annealing and genetic algorithm to manage schedule risk for IT outsourcing projects. Their simulations indicate that the hybrid algorithm was superior to the simulated annealing and genetic algorithm in terms of stability and convergence. Desai and Mohanty (2018) proposed using artificial neural networks to optimize software cost estimation. In addition to a single PM target, Asif and Ahmed (2020) looked at scope, time, and cost. Specifically, they proposed an intelligent system to mitigate software risks from scope, time, and cost for software project managers. Association rule learning, a rule-based ML, was used to find frequent patterns among risk factors and generate risk mitigations.

.

Research on AI in the software project planning process examines solely the scope target. Effort estimation received most of the research attention (Ali et al., 2021; Choetkiertikul et al., 2019; Hammad & Alqaddoumi, 2018; Hosni & Idri, 2017; Ionescu, 2017; Khan et al., 2021; Korenaga et al., 2019; Predescu et al., 2019; Ranković et al., 2021; Suherman et al., 2020; Tamura et al., 2018). These studies adopted various AI techniques, such as linear regression, decision trees, support vector machines, and neural network, to estimate how much effort a project will take to bring to life. Moreover, the sampled research examines other aspects of software project scope, such as requirement management (Anish et al., 2019; Chatterjee et al., 2019, Osman & Zaharin, 2018), human resource management Assavakamhaenghan et al., 2020), team formation (Masuda et al., 2017) and critical success factors (Perera et al., 2021). Overall, AI-based models outperformed tradtional models in providing accurate prediction of the scope target.

The scope target, specifically effort estimation, is also explored in the executing process (Lopez-Martin et al., 2017; Mahfoodh & Hammad, 2020; Oliveira et al., 2021). For instance, Oliveira and colleagues investigated the use of ML to automate issue assignment (aka bug triage) in a global electronics company. They compared different algorithms with the aim of minimizing the time spent and the errors that can arise in the issue assignment process. The performance target is considered, as well. For example, Peña et al. (2019) proposed a method for project execution control partically based on ML techniques (e.g., neural networks and genetic algorithms), and validation of the method ratified an improvement in the quality of project evaluation. Wang and colleagues (2020) designed and implemented a deep learning-based prototype tool for automatic detection and management of technical debt (a suboptimal solution that software developers take shortcuts to achieve rapid delivery during development) in open-source software projects. They demonstrated the effectiveness of the tool over the manual approach.

The performance target is also the focus of the monitoring and controlling process of software projects. Many studies applied AI technologies to predict defects (Eken et al., 2019; Li et al., 2020; Li et al., 2017; Mahfoodh & Obediat, 2020), Pohl et al., 2020; Shrikanth et al., 2021; Tamura & Yamada, 2017. They proved that AI tools could successfully classify bug tickets and predict software defects. AI technologies were also used to predict mature projects in the open source software project community (Liu et al., 2017) and Scrum adoption (Hanslo & Tanner, 2020). The values of AI for PM targets in different PM processes also reverberated in other industries, as ensemble algorithms like the random forests technique were effectively used to evaluate the project performance in transportation and logistics (Li, 2021) and estimate project cost in procurement (García Rodríguez et al., 2019). In sum, the reviewed literature has shown that AI-based models have the capacity to solve dynamic, uncertain, and complex tasks in PM.

.

AI applications can support various PM targets in different PM processes. Compared to the traditional methods, AL methods are more computationally efficient and more accurate in classification, prediction, automation, and optimization.
It is clear that AI technologies are in a pole position to streamline, support, and simplify PM processes and accomplish PM targets.

Research Agenda for AI in PM

Our findings have pointed out avenues for future research to advance AI applications in PM. They indicate that the current PM literature has only looked into ML and NLP of the various AI research areas. ML-powered applications dominated the reviewed papers. The scope of AI-enabled NLP has been limited to a small number of studies that focused on performance targets such as software bug tracking and defect prediction (Eken et al., 2019; Pohl et al., 2020; Shrikanth et al., 2021) or scope targets like requirement management (Anish et al., 2019; Chatterjee et al., 2020; Osman & Zaharin, 2018). More novel NLP applications in PM need more systematic research, considering the various NLP capabilities in content categorization, topic discovery, sentiment analysis, document summarization, and machine translation. For example, future research can explore NLP-enabled chatbots to effectively handle routine project management tasks such as scheduling, reminder, and follow-ups to eliminate the need for human input. Future research can also investigate how other AI research areas (e.g., knowledge representation) can be incorporated into PM. Such AI applications can be valuable in contributing to the success of PM across the project, the project teams, and its cultural environments, such as a dynamic product definition, improved collaboration and communication, and management buy-in (Noteboom et al., 2021).
Moreover, our analysis uncovers some issues with data, which are the lifeblood of AI applications. Big data that have enabled the recent AI advances boasts not only structured data, such as transactional data in a relational database, but also unstructured data from audio, images, video, and so on (Constantiou & Kallinikos, 2015). However, existing AI applications in PM have relied heavily on textual data. In other words, the unstructured data are hardly analyzed. Future research needs to consider the impacts of unstructured data on AI applications in PM. Again, take NLP, for example. The recent breakthroughs in speech recognition make voice NLP applications valuable to automate some verbal communications to improve PM operational efficiency. Voice NLP applications can also free up significant time for project managers and team members from recording and reporting to working on their deliverables. In addition, hidden in the diverse unstructured data is valuable information that can be turned into meaningful actions.

.

Our review shows that AI applications fed on textual data are powerful in predicting time, cost, scope, and performance targets. Unstructured data can be used for prediction, as well.

Most reviewed research has worked on small numbers of data. This may explain why only supervised ML techniques are employed in the sampled literature. Unsupervised ML's capability to learn without human input requires extremely large datasets. It scales much better with more data than its supervised counterpart. While supervised ML typically plateaus in performance after it reaches a threshold of data, the performance of unsupervised ML continues to improve when exposed to more data. Future research needs to work on more sizable data for more robust models, valid statistical inferences, and powerful outcomes.

In addition, while the reviewed literature stresses the technical superiority of AI technology in PM, it does not pay attention to some critical concerns that can hinder the progress of AI in PM. One such concern is the need for more transparency in AI algorithms. Although what information is put together and goes in a non-proprietary AI application is known, it usually goes unexplained how the algorithm reaches its conclusions (Castelvecchi, 2016).). DL algorithms can be particularly opaque because they continuously tweak their parameters and rules as they learn. As AI algorithms adapt over time, they are then not only opaque but also likely to change over time. This black box problem of AI algorithms creates problems in validating the outputs of AI applications and identifying errors or biases in the data (Adadi & Berrada, 2018). It can make project managers skeptical about AI applications as they cannot understand the rationale of AI applications. To expand the use of AI in PM, future research needs to explore how to open the black box mystery to gain the trust of project managers.

Trust can also be compromised by the reliability of AI applications (Shneiderman, 2020). AI applications go through training and testing phases. However, the training and testing phases can only cover some possible scenarios that an AI application may encounter in the real world. And AI technologies could make mistakes. In addition, an AI application can be fooled in ways that humans would not be. For example, random dot patterns can lead a machine to 'see' things that are not there. AI technologies could make errors. The stake of mistakes and errors can be high in PM. Future research needs to improve the reliability of AI applications before the large-scale adoption of AI technologies in PM becomes a reality.

Significance to Practitioners

Our research is significant for PM practitioners. First, it helps project managers and team members understand the basics of AI technologies. Given the rapid pace with which AI is being developed, many definitions, terms, and phrases have been used to describe AI technologies.

.

Our review surveys major AI technologies (e.g., ML, NLP) and techniques (e.g., neural networks, ensemble) and how they are related (e.g., supervised vs. unsupervised learning). Such conceptual explanations can give PM practitioners interested in AI an understanding necessary to comprehend AI applications in PM. Second, our findings can stimulate more interest in applying AI to PM. AI applications' success in managing software, construction, and energy projects can encourage PM teams in other areas to embrace and adopt AI technologies. Our findings can also guide future implementation of AI applications as they show where AI technologies and techniques can serve the project's needs and improve project success.

LIMITATIONS

The current study is not without its limitations. Most notably, a limitation in most reviews, such as this one, relates to the sampling. The publication rate in AI applications in PM is fast increasing, and our review may have difficulty keeping up with new developments. Nevertheless, this review provides a general scope of AI applications in PM. Second, we only analyzed full-text papers written in English. Though our review is representative of AI applications in PM in the last five years, it may miss some development in the dynamic and fast-paced research reported in languages other than English. Finally, our review focused on the PM processes and targets and did not capture the impacts of AI applications on other aspects of PM (e.g., the skills required for project managers).

CONCLUSION

AI has emerged as the defining technology of the 21st century (Liu et al., 2018). AI technologies have been undergoing tremendous and rapid advancements in recent years (Whittaker et al., 2018). They can draw distinctions invisible to the naked eye, analyze data and uncover patterns that elude human observers, and have the advantage of efficiency and effectiveness (Chen, 2013). As such, AI technologies are finding a home in many areas, including PM. With the ability to automate routine activities and unlock new insights, AI can disrupt PM at an unprecedented scale and has become a budding area of research in PM (Auth et al., 2019).

This paper presents a systematic analysis of research on the applications of AI technologies in PM in the last five years. It has provided encouraging results that AI applications improve PM processes and targets compared to traditional methods. This paper helps researchers and practitioners understand AI's status in the PM domain. Equally important, it highlights important areas of AI-powered research to

.

move the PM field forward. Success in AI and PM requires a focus on integrating two fast-growing fields. It needs technical AI domain expertise and PM discipline knowledge. AI applications in PM are promising, and much more systematic research is necessary for the practical or commercial implementation of AI-driven PM.

REFERENCES

* indicating the sampled papers

Aerts, A., & Bogdan-Martin, D. (2021). Leveraging data and AI to deliver on the promise of digital health. *International Journal of Medical Informatics*, 150, 104456.

Adadi, A., & Berrada, M. (2018). Peeking inside the black box: A survey on explainable artificial intelligence (XAI). *IEEE Access*, 6, 52138-52160.

Ahmed, S., & El-Sayegh, S. (2020). Critical review of the evolution of project delivery methods in the construction industry. *Buildings*, 11(1), 11.

* Ajayi, A., Oyedele, L., Owolabi, H., Akinade, O., Bilal, M., Davila Delgado, J. M., & Akanbi, L. (2020). Deep Learning models for health and safety risk prediction in power infrastructure projects. *Risk Analysis*, 40(10), 2019–2039.

* Ali, Z., Israr ur Rehman, & Zahoor Jaan. (2021). An Empirical analysis of software development efforts estimation in machine learning perspective. *Advances in Distributed Computing and Artificial Intelligence Journal*, 10(3), 227–240.

* Anish, P. R., Sainani, A., Ahmed, A., & Ghaisas, S. (2019). Implementation-centric classification of business rules from documents. *2019 IEEE 27th International Requirements Engineering Conference Workshops (REW)*, 227–233.

* Arage, S. S., & Dharwadkar, N. V. (2017). Cost estimation of civil construction projects using machine learning paradigm. *2017 International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*, 594–599.

.

* Asif, M., & Ahmed, J. (2020). A novel case base reasoning and frequent pattern based decision support system for mitigating software risk factors. *IEEE Access*, 8, 102278–102291.

* Assavakamhaenghan, N., Suwanworaboon, P., Tanaphantaruk, W., Tuarob, S., & Choetkiertikul, M. (2020). Towards team formation in software development: A case study of Moodle. *2020 17th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON),* 157–160.

Auth, G., Jokisch, O., & Dürk, C. (2019). Revisiting automated project management in the digital age–a survey of AI approaches. *Online Journal of Applied Knowledge Management,* 7(1), 27-39.

Auth, G., Jöhnk, J., & Wiecha, D. A. (2021). A conceptual framework for applying artificial intelligence in project management. *2021 IEEE 23rd Conference on Business Informatics (CBI),* 01, 161–170.

* Bai, L., Wang, Z., Wang, H., Huang, N., & Shi, H. (2021). Prediction of multiproject resource conflict risk via an artificial neural network. *Engineering, Construction and Architectural Management*, 28(10), 2857–2883.

* BaniMustafa, A. (2018). Predicting software effort estimation using machine learning techniques. *2018 8th International Conference on Computer Science and Information Technology (CSIT),* 249–256.

Bench-Capon, T. J. (2014). Knowledge representation: An approach to artificial intelligence (Vol. 32). Elsevier.

Bertossi, L., & Geerts, F. (2020). Data quality and explainable AI. *Journal of Data and Information Quality*, 12(2), 1-9.

* Buah, E., Linnanen, L., Wu, H., & Kesse, M. A. (2020). Can artificial intelligence assist project developers in long-term management of energy projects? The case of CO_2 capture and storage. *Energies*, 13(23), 6259.

Canhoto, A. I., & Clear, F. (2020). Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential. *Business Horizons*, 63(2), 183-193.

.

Castelvecchi, D. (2016). Can we open the black box of AI?. *Nature News*, 538(7623), 20.

* Chatterjee, R., Ahmed, A., & Anish, P. R. (2020). Identification and classification of architecturally significant functional requirements. *2020 IEEE Seventh International Workshop on Artificial Intelligence for Requirements Engineering (AIRE)*, 9–17.

Chen, C. H. (Ed.). (2013). *Pattern Recognition and Artificial Intelligence*. Elsevier.

* Choetkiertikul, M., Dam, H. K., Tran, T., Pham, T., Ghose, A., & Menzies, T. (2019). A deep learning model for estimating story points. *IEEE Transactions on Software Engineering*, 45(7), 637–656.

* Choi, S., Lee, E.-B., & Jong-Hyun, K. (2021). The engineering machine-learning automation platform (EMAP): A big-data-driven ai tool for contractors' sustainable management solutions for plant projects. *Sustainability*, 13(18), 10384.

Constantiou, I. D., & Kallinikos, J. (2015). New games, new rules: Big data and the changing context of strategy. *Journal of Information Technology*, 30(1), 44–57.

Dam, H. K., Tran, T., Grundy, J., Ghose, A., & Kamei, Y. (2019). Towards effective AI-powered agile project management. *The 41st International Conference on Software Engineering: New Ideas and Emerging Results*, 41–44.

Davenport, T. H. (2018). *The AI advantage: How to Put the Artificial Intelligence Revolution to Work*. Cambridge, MA: MIT Press.

* De Carvalho, H. D. P., Fagundes, R., & Santos, W. (2021). Extreme learning machine applied to software development effort estimation. *IEEE Access*, 9, 92676–92687.

* Desai, V. S., & Mohanty, R. (2018). ANN-Cuckoo optimization technique to predict software cost estimation. *2018 Conference on Information and Communication Technology (CICT)*, 1–6.

Do, H. P., Do, N. V., & Nguyen, H. D. (2019). A consulting system for estimating costs of an information technology hardware project based on law of

.

public investment. *2019 International Conference on System Science and Engineering (ICSSE)*, 285–290.

* Dritsas, E., Fazakis, N., Kocsis, O., Moustakas, K., & Fakotakis, N. (2021). Optimal team pairing of elder office employees with machine learning on synthetic data. *2021 12th International Conference on Information, Intelligence, Systems Applications (IISA)*, 1–4.

* Eken, B., Atar, R., Sertalp, S., & Tosun, A. (2019). Predicting defects with latent and semantic features from commit logs in an industrial setting. *2019 34th IEEE/ACM International Conference on Automated Software Engineering Workshop (ASEW)*, 98–105.

* Elmousalami, H. H. (2021). Comparison of artificial intelligence techniques for project conceptual cost prediction: A case study and comparative analysis. *IEEE Transactions on Engineering Management*, 68(1), 183–196.

Fridgeirsson, T. V., Ingason, H. T., Jonasson, H. I., & Jonsdottir, H. (2021). An authoritative study on the near future effect of artificial intelligence on project management knowledge areas. *Sustainability*, 13(4), 2345.

* García Rodríguez, M. J., Vicente Rodríguez Montequín, Francisco Ortega Fernández, & Villanueva Balsera, J. M. (2019). Public procurement announcements in spain: Regulations, data analysis, and award price estimator using machine learning. *Complexity*, 2019, 20.

Halper, F. (2017). Advanced analytics: Moving toward AI, machine learning, and natural language processing. *TDWI Best Practices Report*.

* Hammad, M., & Alqaddoumi, A. (2018). Features-level software effort estimation using machine learning algorithms. *2018 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT)*, 1–3.
* Hanslo, R., & Tanner, M. (2020). Machine learning models to predict agile methodology adoption. *2020 15th Conference on Computer Science and Information Systems (FedCSIS)*, 697–704.

Heagney, J. (2016). *Fundamentals of Project Management*. Amacom.

Hendler, J. A., Tate, A., & Drummond, M. (1990). AI planning: Systems and techniques. *AI Magazine*, 11(2), 61–61.

.

* Hosni, M., & Idri, A. (2017). Software effort estimation using classical analogy ensembles based on random subspace. *2017 Symposium on Applied Computing*, 1251–1258.

* Ionescu, V.-S. (2017). An approach to software development effort estimation using machine learning. *2017 13th IEEE International Conference on Intelligent Computer Communication and Processing (ICCP)*, 197–203.

* Kareem Kamoona, K. R., & Budayan, C. (2019). Implementation of genetic algorithm integrated with the deep neural network for estimating at completion simulation. *Advances in Civil Engineering*, 2019, 7081073.

* Khan, M. S., Jabeen, F., Ghouzali, S., Rehman, Z., Naz, S., & Abdul, W. (2021). Metaheuristic algorithms in optimizing deep neural network model for software effort estimation. *IEEE Access*, 9, 60309–60327.

Kok, J. N., Boers, E. J., Kosters, W. A., Van der Putten, P., & Poel, M. (2009). Artificial intelligence: Definition, trends, techniques, and cases. *Artificial Intelligence*, 1, 270-299.

* Korenaga, K., Monden, A., & Yücel, Z. (2019). Data smoothing for software effort estimation. *2019 20th IEEE/ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD)*, 501–506.

Kroenke, D. M., & Boyle, R. J. (2021). *Using MIS* (12th edition). Pearson.

Lee, W. J. (2020). A study on word cloud techniques for analysis of unstructured text data. *Journal of the Convergence on Culture Technology*, 6(4), 715-720.

* Li, H. (2021). Data-driven public r&d project performance evaluation: Results from China. *Sustainability*, 13(13), 7147.

* Li, K., Xiang, Z., Chen, T., & Tan, K. C. (2020). BiLO-CPDP: Bi-level programming for automated model discovery in cross-project defect prediction. *2020 35th IEEE/ACM International Conference on Automated Software Engineering (ASE)*, 573–584.

* Li, Y., Huang, Z., Wang, Y., & Fang, B. (2017). Evaluating data filter on cross-project defect prediction: comparison and improvements. *IEEE Access*, 5, 25646–25656.

.

Liberati, A., Altman, D. G., Tetzlaff, J., Mulrow, C., Gøtzsche, P. C., Ioannidis, J. P., Clarke, M., Devereaux, P. J., Kleijnen, J., & Moher, D. (2009). The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration. *PLoS Medicine*, 6(7), e1000100.

* Lin, T., Tao, Y., Zhang, C., & Liu, J. (2019). Intelligent prediction of the construction cost of substation projects using support vector machine optimized by particle swarm optimization. *Mathematical Problems in Engineering*, 2019, 1-10.

Liu, J., Kong, X., Xia, F., Bai, X., Wang, L., Qing, Q., & Lee, I. (2018). Artificial intelligence in the 21st century. *IEEE Access*, 6, 34403-34421.

* Liu, Q., Li, X., Zhu, H., & Fan, H. (2017). Acquisition of open source software project maturity based on time series machine learning. *2017 10th International Symposium on Computational Intelligence and Design (ISCID)*, 1, 296–299.

* Lopez-Martin, C., Banitaan, S., Garcia-Floriano, A., & Yanez-Marquez, C. (2017). Support vector regression for predicting the enhancement duration of software projects. *2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA)*, 562–567.

Louridas, P., & Ebert, C. (2016). Machine learning. *IEEE Software*, 33, 110–115.

* Lu, F., Bi, H., Huang, M., & Duan, S. (2017). Simulated annealing genetic algorithm based schedule risk management of IT outsourcing project. *Mathematical Problems in Engineering*, 2017, 17.

* Ma, S., & Deng, S. S. (2021). Research on software project scheduling based on genetic algorithm. *2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE)*, 67–70.

* Mahfoodh, H., & Hammad, M. (2020). Bug-fix time prediction using non-linear regression through neural network. *The 3rd Smart Cities Symposium (SCS 2020)*, 622–627.

* Mahfoodh, H., & Obediat, Q. (2020). Software risk estimation through bug reports analysis and bug-fix time predictions. *2020 International*

.

Conference on Innovation and Intelligence for Informatics, Computing and Technologies (3ICT), 1–6.

Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, 90, 46–60.

* Masuda, A., Matsuodani, T., & Tsuda, K. (2017). A comparative study using discriminant analysis on a questionnaire survey regarding project managers' cognition and team characteristics. *2017 IEEE 41st Annual Computer Software and Applications Conference (COMPSAC)*, 643–648.

Munns, A., & Bjeirmi, B. (1996). The role of project management in achieving project success. *International Journal of Project Management*, 14(2), 81–87.

Murphy, R. R. (2019). *Introduction to AI Robotics*. Cambridge, MA.: MIT Press.

Noteboom, C., Ofori, M., Sutrave, K., & El-Gayar, O. (2021). Agile project management: A systematic literature review of adoption drivers and critical success factors. *2021 Hawaii International Conference on System Sciences (HICSS 2021)*, 6675-6784.

* Oliveira, P., Andrade, R. M. C., Barreto, I., Nogueira, T. P., & Morais Bueno, L. (2021). Issue auto-assignment in software projects with machine learning techniques. *2021 IEEE/ACM 8th International Workshop on Software Engineering Research and Industrial Practice (SER IP)*, 65–72.

Ong, S., & Uddin, S. (2020). Data science and artificial intelligence in project management: the past, present and future. *Journal of Modern Project Management*, 7(4), 27-33.

* Osman, M. H., & Zaharin, M. F. (2018). Ambiguous software requirement specification detection: an automated approach. *2018 IEEE/ACM 5th International Workshop on Requirements Engineering and Testing (RET)*, 33–40.

* Owolabi, H. A., Bilal, M., Oyedele, L. O., Alaka, H. A., Ajayi, S. O., & Akinade, O. O. (2020). Predicting completion risk in ppp projects using big data analytics. *IEEE Transactions on Engineering Management*, 67(2), 430–453.

.

Pan, Y. (2016). Heading toward artificial intelligence 2.0. *Engineering*, 2(4), 409-413.

* Peña, A. B., Castro, G. F., Alvarez, D. M. L., Alcivar, I. A. M., Núñez, G. L., Cevallos, D. S., & Santa, J. L. Z. (2019). Method for project execution control based on soft computing and machine learning. *2019 XLV Latin American Computing Conference (CLEI)*, 1–7.

* Perera, A. D., Jayamaha, N. P., Grigg, N. P., Tunnicliffe, M., & Singh, A. (2021). The application of machine learning to consolidate critical success factors of lean six sigma. *IEEE Access*, 9, 112411–112424.

Peixoto, B., Pinto, R., Melo, M., Cabral, L., & Bessa, M. (2021). Immersive virtual reality for foreign language education: A PRISMA systematic review. *IEEE Access*, 9, 48952-48962.

* Pohl, M., Hashaam, A., Bosse, S., Staegemann, D. G., Volk, M., Kramer, F., & Turowski, K. (2020). Application of NLP to determine the State of Issues in Bug Tracking Systems. *2020 International Conference on Data Mining Workshops (ICDMW)*, 53–61.

* Predescu, E.-F., Tefan, A., & Zaharia, A.-V. (2019). Software effort estimation using multilayer perceptron and long short term memory. *Informatica Economica*, 23(2), 76–87.

Project Management Institute. (2017). *A Guide to the Project Management Body of Knowledge (PMBOK® Guide)* (Sixth Edition). Project Management Institute.

* Ranković, N., Ranković, D., Ivanović, M., & Lazić, L. (2021). Artificial neural network architecture and orthogonal arrays in estimation of software projects efforts. *2021 International Conference on INnovations in Intelligent SysTems and Applications (INISTA)*, 1–6.

Regona, M., Yigitcanlar, T., Xia, B., & Li, R. Y. M. (2022). Opportunities and adoption challenges of AI in the construction industry: a PRISMA review. *Journal of Open Innovation: Technology, Market, and Complexity*, 8(1), 45.

Schoper, Y.-G., Wald, A., Ingason, H. T., & Fridgeirsson, T. V. (2018). Projectification in Western economies: A comparative study of Germany,

.

Norway and Iceland. *International Journal of Project Management*, 36(1), 71–82.

Shen, Z. (2020). Natural language processing (nlp) applications in patient care: A systematic analysis. *Quarterly Review of Business Disciplines*, 7(3), 223–244.

Shneiderman, B. (2020). Human-centered artificial intelligence: Reliable, safe & trustworthy. *International Journal of Human–Computer Interaction*, 36(6), 495-504.

* Shrikanth, N. C., Majumder, S., & Menzies, T. (2021). Early life cycle software defect prediction. Why? How? *2021 IEEE/ACM 43rd International Conference on Software Engineering (ICSE)*, 448–459.

* Suherman, I. C., Sarno, R., & Sholiq. (2020). Implementation of random forest regression for COCOMO II effort estimation. *2020 International Seminar on Application for Technology of Information and Communication (ISemantic)*, 476–481.

Szeliski, R. (2022). *Computer Vision: Algorithms and Applications*. Springer Nature.

* Tamura, Y., Sone, H., Sugisaki, K., & Yamada, S. (2018). effort analysis of OSS project based on deep learning considering UI/UX design. *2018 7th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)* (ICRITO), 1–6.

* Tamura, Y., & Yamada, S. (2017). Reliability and maintainability analysis and its toolbased on deep learning for fault big data. *2017 6th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*, 106–111.

Uchihira, N., Mori, T., & Oshima, T. (2020). Artificial intelligence and project management. *IEICE ESS Fundamentals Review*, 13(4), 277–283.

* Wang, X., Liu, J., Li, L., Chen, X., Liu, X., & Wu, H. (2020). Detecting and explaining self-admitted technical debts with attention-based neural networks. *2020 35th IEEE/ACM International Conference on Automated Software Engineering (ASE)*, 871–882.

.

Whittaker, M., Crawford, K., Dobbe, R., Fried, G., Kaziunas, E., Mathur, V., West, S., Richardson, R., Schultz, J., & Schwartz, O. (2018). *AI Now Report 2018*. New York: AI Now Institute at New York University.

William, P., Kumar, P., Chhabra, G. S., & Vengatesan, K. (2021). Task allocation in distributed agile software development using machine learning approach. *2021 International Conference on Disruptive Technologies for Multi-Disciplinary Research and Applications (CENTCON)*, 1, 168–172.

Yang, M. (2021). Design of project cost information management system based on intelligent construction. *Journal of Physics: Conference Series*, 1881(4), 042084.

* Yaseen, Z. M., Ali, Z. H., Salih, S. Q., & Al-Ansari, N. (2020). Prediction of risk delay in construction projects using a hybrid artificial intelligence model. *Sustainability*, 12(4), 1514.

* Zhang, S., & Wang, X. (2021). Dynamic probability analysis for construction schedule using subset simulation. *Advances in Civil Engineering*, 2021, 1-13.

* Zhong, Y., Li, H., & Chen, L. (2021). Construction project risk prediction model based on EW-FAHP and one dimensional convolution neural network. *PLoS One*, 16(2), e0246539.

APPENDIX: SUMMARY OF CODINGS

.

Study	Industry	PM Process	PM Target	AI Area	AI Techniques	Data Source	Data Size	Outlet	Year
Ajayi et al., 2020	Energy	Initiating	Scope *Risk prediction*	ML	Deep Neural Networks	Health & Safety (UK)	17,972 (16,900 after cleaning)	jouranl	2020
Ali et al., 2021	IT/Software Development	Planning	Scope *Effort estimation*	ML	Decision Trees; Ridge Regression; Others	Albrecht Dataset, Desharnais Dataset, COCOMO Dataset, NASA Dataset, Kemerer Dataset, China Dataset, Kitchenham Dataset	24 projects; 81 projects; 63 projects; 93 projects; 15 projects; 499 projects; 145 projects	journal	2021
Anish et al., 2019	IT/Software Development	Planning	Scope *Requirements management*	NLP	Recurrent Neural Networks	SRS Documents	40 documents	conference	2019
Arage & Dharwadkar, 2017	Construction	Initiating	Cost *Cost prediction*	ML	Linear Regression Model	Construction projects (India)	813 samples	conference	2017
Asif & Ahmed, 2020	IT/Software Development	Initiating	Scope *Risk prediction*	ML	Case-based Reasoning	Case studies	40 studies	journal	2020
Assavakamhaenghan et al., 2020	IT/Software Development	Planning	Scope *Human resource management*	ML	Logistic Regression; MaxLogit Algorithm	JIRA Data (JIRA Data for Moodle)	80,000 issues	conference	2020
Bai et al., 2021	Project/ Program Management	Planning	Scope *Risk management*	ML	Artificial Neural Networks	Survey	193 survey responses	journal	2021
BaniMustafa, 2018	IT/Software Development	Planning	Scope *Effort estimation*	ML	Random Forests; Naive Bayes; Logistic Regression	NASA Dataset	93 projects	conference	2018
Buah et al., 2020	Energy	Executing	Scope *Communication management*	NLP	Deep Neural Networks	Hypothetical CO2 storage projects	198 projects	journal	2020
Chatterjee et al., 2020	IT/Software Development	Planning	Scope *Requirements management*	NLP	Recurrent Neural Networks	SRS Documents	124 documents (9233 sentences)	conference	2020

Choetkiertikul et al., 2019	IT/Software Development	Planning	Scope *Effort estimation*	ML	Recurrent Neural Networks	Story points	23,313 user stories	journal	2019
Choi et al., 2021	Construction	Initiating	Cost *Cost prediction*	NLP	Recurrent Neural Networks; Decision Tree; Random Forests; Gradient Boosting; XGBoost	Industrial sites (contract risks and technical risks of EPC projects from 2000 to 2018 in the Middle East, South America, North America, West Africa, the North Sea, and Australia)	19 plant contracts and 10 SoW documents	journal	2021
Desai & Mohanty, 2018	IT/Software Development	Initiating	Cost *Cost prediction*	ML	Artificial Neural Networks	ISBSG Dataset (International Software Benchmarking Standards Group)	4,106 projects	journal	2021
Dritsas et al., 2021	Human Resources	Planning	Scope *Human resource management*	ML	M5P Regressor	Synthetic dataset	350 employees, 50 projects, 7 occupations; 28 skills	conference	2021
Eken et al., 2019	IT/Software Development	Monitoring & Controlling	Performance *Defect prediction*	NLP	Naive Bayes; XGBoost	Git repository; JIRA Data (commits)	2,299 commits	conference	2019
Elmousalami, 2021	Farming/ Agriculture	Initiating	Cost *Cost prediction*	ML	XGBoost; Others	FCIP (Field canals improvement projects)	144 projects	journal	2021
Garcia Rodriguez et al., 2019	Procurement	Initiating	Cost *Cost prediction*	ML	Random Forests	Public tenders (Spain)	58,337 tenders	journal	2019
Hammad & Alqaddoumi, 2018	IT/Software Development	Planning	Scope *Effort estimation*	ML	Support Vector Machines; Others	Usp05-tf	76 projects	conference	2018
Hanslo & Tanner, 2020	IT/Software Development	Monitoring & Controlling	Performance *Scrum adoption prediction*	ML	Multiple Linear Regression	Survey	207 survey responses	conference	2020

Hosni & Idri, 2017	IT/Software Development	Planning	Scope *Effort estimation*	ML	Random Space Classical Analogy; Classical Analogy	Albrecht Dataset;COCOMO Dataset;China Dataset;Desharnais Dataset;ISBSG Dataset;Kemerer Dataset;Miyazaki Dataset	24 projects; 252 projects; 499 projects; 77 projects; 148 projects; 15 projects; 48 projects;	conference	2017
Ionescu, 2017	IT/Software Development	Planning	Scope *Effort estimation*	ML	Artificial Neural Networks	Instances (Instance describes a task)	7,826 instances	conference	2017
Kareem Kamoona & Budayan, 2019	Construction	Initiating	Cost *Cost prediction*	ML	Genetic Algorithm; Deep Neural Networks	Construction projects (Iraq)	15 projects	journal	2019
Khan et al., 2021	IT/Software Development	Planning	Scope *Effort estimation*	ML	Deep Neural Networks	NASA Dataset; COCOMO Dataset; Maxwell Dataset	93 projects; 63 projects; 62 projects	journal	2021
Korenaga et al., 2019	IT/Software Development	Planning	Scope *Effort estimation*	ML	k-Nearest Neighbors	Albrecht Dataset; China Dataset; COCOMO Dataset; Desharnais Dataset; Kemerer Dataset; Kitchenham Dataset; Maxwell Dataset; Miyazaki Dataset	24 projects; 499 projects; 63 projects; 81 projects; 15 projects; 145 projects; 62 projects; 48 projects	conference	2019
Li, 2021	Transportation/ Logistics	Monitoring & Controlling	Performance *Performance evaluation*	ML	Random Forests; Others	National Natural Science Foundation of China (NFSC) website	1,199 samples	journal	2021
Li et al., 2020	IT/Software Development	Monitoring & Controlling	Performance *Defect prediction*	ML	Bilevel Optimization	JURECZKO; AEEEM; ReLink	20 projects – 12 (Jureczko); 5 (AEEEM); 3 (ReLink)	conference	2020
Li et al., 2017	IT/Software Development	Monitoring & Controlling	Performance *Defect prediction*	ML	Naive Bayes; Support Vector Machine	JURECZKO	14 projects (44 releases)	journal	2017
Lin et al., 2019	Construction	Initiating	Cost *Cost prediction*	ML	Support Vector Machine; Particle Swam Optimization	Construction projects (China)	65 data samples	journal	2019

.

Liu et al., 2017	IT/Software Development	Monitoring & Controlling	Performance *Maturity prediction*	ML	Support Vector Machines	GitHub	40 projects	conference	2017
Lopez-Martin et al., 2017	IT/Software Development	Executing	Scope *Effort estimation*	ML	Support Vector Regression	ISBSG Dataset	5052 projects	conference	2017
Lu et al., 2017	IT/Software Development	Initiating	Time *Schedule management*	ML	Simulated Annealing; Genetic Algorithm	N/A	N/A	journal	2017
Ma & Deng, 2021	IT/Software Development	Initiating	Time *Schedule management*	ML	Genetic Algorithm	N/A	N/A	conference	2021
Mahfoodh & Hammad, 2020	IT/Software Development	Executing	Scope *Effort estimation*	ML	Artificial Neural Networks	Mozilla Firefox; Mozilla Core; Eclipse platform; AspectJ; Birt; Eclipse platform UI; JDT; SWT; Tomcat	19,271 samples; 101,500 samples; 42,415 samples; 578 samples; 975 samples; 2,031 samples; 3,803 samples; 3,739 samples; 1,036 samples	conference	2020
Mahfoodh & Obediat, 2020	IT/Software Development	Monitoring & Controlling	Performance *Defect prediction*	ML	Artificial Neural Networks	Mozilla Core	101, 500 bug samples (44,692 duplicated bugs)	conference	2020
Masuda et al., 2017	IT/Software Development	Planning	Scope *Team formation*	ML	Discriminant Analysis	Companies (Case A); PM Symposium 2013 (Case B)	20 project groups; 55 project groups	conference	2017
Oliveira et al., 2021	IT/Software Development	Executing	Scope *Effort estimation*	NLP	Stochastic Gradient Descent with Text; Logistic Regression; Random Forests	Issue tracking system	8,344 issues (5684 useful issues)	conference	2021
Osman & Zaharin, 2018	IT/Software Development	Planning	Scope *Requirements management*	NLP	Random Forests	SRS documents (Malaysia)	4 SRS documents; 4 project groups	conference	2018
Owolabi et al., 2020	Construction	Initiating	Scope *Risk prediction*	ML	Random Forests	PPP projects (UK)	4,294 projects	journal	2020

Peña et al., 2019	IT/Software Development	Executing	Performance *Execution control*	ML	Fuzzy Logic; Artificial Neural Networks; Gradint Descent Optimization	GESPRO (project management platform)	204 finished projects	conference	2019
Perera et al., 2021	IT/Software Development	Planning	Scope *Critical Success Factors*	NLP	Deep Neural Networks	Academic literature	19 articles	journal	2021
Pohl et al., 2020	IT/Software Development	Monitoring & Controlling	Performance *Defect prediction*	NLP	Support Vector Machines	Software development tickets	2,217 tickets	conference	2020
Predescu et al., 2019	IT/Software Development	Planning	Scope *Effort estimation*	ML	Recurrent Neural Networks	Desharnais Dataset	77 projects	journal	2019
Ranković et al., 2021	IT/Software Development	Planning	Scope *Effort estimation*	ML	Artificial Neural Networks	Software projects	194 projects	conference	2021
Shrikanth et al., 2021	IT/Software Development	Monitoring & Controlling	Performance *Defect prediction*	NLP	Logistic Regression; k-Nearest Neighbors; Decision Trees; Random Forests; Naive Bayes; Support Vector Machines	GitHub	155 projects	conference	2021
Suherman et al., 2020	IT/Software Development	Planning	Scope *Effort estimation*	ML	Random Forests Regression	NASA Dataset	93 project attributes	conference	2020
Tamura et al., 2018	IT/Software Development	Planning	Scope *Effort estimation*	ML	Deep Neural Networks	Apache (Bug tracking system on the website of Apache)	10,000 fault data sets	conference	2018
Tamura & Yamada, 2017	IT/Software Development	Monitoring & Controlling	Performance *Defect prediction*	ML	Deep Neural Networks	Apache (Bug tracking system of Apache HTTP server)	10,000 fault data sets	conference	2017
Wang et al., 2020	IT/Software Development	Executing	Time *Technical Debt* Prediction	NLP	Recurrent Neural Networks	Software development projects	20 projects (445,365 SATD comments)	conference	2020
Yaseen et al., 2020	Construction	Executing	Scope *Risk prediction*	ML	Random Forests; Genetic Algorithm	Construction projects (Iraq)	40 projects	journal	2020
Zhang & Wang, 2021	Construction	Initiating	Time *Schedule management*	ML	Statistical Learning; Gradient Descent Optimization	Construction projects	194 activities	journal	2021
Zhong et al., 2021	Construction	Initiating	Scope *Risk prediction*	ML	Convolution Neural Networks	Construction projects (China)	40 projects	journal	2021