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Artificial Intelligence Enabled Project Management: A Systematic Literature Review

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Abstract: In the Industry 5.0 era, companies are leveraging the potential of cutting-edge technologies such as artificial intelligence for more efficient and green human-centric production. In a similar approach, project management would benefit from artificial intelligence in order to achieve project goals by improving project performance, and consequently, reaching higher sustainable success. In this context, this paper examines the role of artificial intelligence in emerging project management through a systematic literature review; the applications of AI techniques in the project management performance domains are presented. The results show that the number of influential publications on artificial intelligence-enabled project management has increased significantly over the last decade. The findings indicate that artificial intelligence, predominantly machine learning, can be considerably useful in the management of construction and IT projects; it is notably encouraging for enhancing the planning, measurement, and uncertainty performance domains by providing promising forecasting and decision-making capabilities.

Keywords: artificial intelligence; project management; project performance domains; Industry 5.0

1. Introduction

The worldwide COVID-19 pandemic highlighted the need to rethink existing working methods and approaches and has intensified the vulnerabilities of the industries, showing that more human-centric and sustainable solutions are required. The current transition from the "old normal" to the "new normal" can be observed as an opportunity to reshape and renew the role of the industry in society. In this context, the emerging Industry 5.0 concept was released [1].

Industry 5.0 is based on Industry 4.0, which was first defined in Germany in 2011 as part of the country's high-tech strategy. Industry 4.0's principles are the integration of digital technologies for automation and data exchange in the manufacturing process; that is, it combines production methods with information and communication technologies such as Artificial Intelligence (AI). Furthermore, Industry 5.0 pursues to leverage the potential of technologies, such as advanced digitalization, AI and big data (BD), in the same way Industry 4.0 does, but deploying solutions for a more human-centric, sustainable, and resilient industry.

Breque et al. [1] point out that AI is one of the enabling technologies that will help shift to Industry 5.0; however, AI is not a new field. After World War II, several people started working on intelligent machines. Alan Turing may have been the first person researching AI in as early as 1947 [2]. Since then, AI has had several tops and downs and nowadays is in a new hype phase. For instance, AI is being used in novel scenarios such as the COVID-19 pandemic for the early detection and diagnosis of patients and in the development of drugs and vaccines [3].

It is important to note that it is not only manufacturing processes that will benefit from the application of new technologies: business procedures such as project management (PM)

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that are crucial in the daily operation of an organization are also expected to benefit from them. In fact, cutting-edge PM trends focus on the use of AI at work. PMI [4] discusses the role of AI in PM, highlighting that AI changes the types of projects being delivered and also how they are managed. Although such reports highlight that project leaders say that AI technologies are encouraging PM productivity and enhancing the quality of work, there are no studies covering this topic in the literature that focus on the analysis of AI techniques in the different PM performance domains (PDs) [5]. So, the question arises as to how AI will be able to boost PMPDs and procedures; and thus how the literature will develop to this end.

To the best of our knowledge, there has been no systematic literature review (SLR) of the application of AI technologies in PMPDs, which are introduced in the Project Management Body of Knowledge 7th edition (PMBOK7). Therefore, the goal of this paper is to explore the role of AI in emerging PM by analyzing the literature based on the PMPDs. This novel approach has not been previously explored in the literature, and our review provides insights into how AI techniques can be aligned with each of the PMPDs to enhance project performance. This unique contribution sets our paper apart from previous literature reviews.

The rest of the paper is organized as follows. Section 2 provides an introduction to AI technologies and cutting-edge PM techniques. Then, in Section 3, the methodology conducted in this research is described, and in Section 4, the bibliometric analysis and the literature review are developed. Later, Section 5 discusses the findings obtained, and, finally, in Section 6, the conclusions of the paper are given.

2. Related Work

2.1. Hints on AI Basics

There is an ongoing discussion of how to define AI. In fact, there are different approaches when defining it [6]: on the one hand some researchers aim at introducing human minds' capacities into computers and on the other hand there is a trend to understand AI as the science of making intelligent machines, not necessarily with methods that are biologically observable.

Historically, four perspectives of AI have been followed [6] and laid out along two dimensions: thinking (concerned with thought processes and reasoning) and acting (addresses behavior). In addition, two different philosophies can be followed: a human-centered approach that involves observations and hypotheses about human behavior or a rationalist approach, namely a combination of mathematics and engineering.

Thanks to its potential, AI can be used for innumerable purposes and fields such as healthcare [7], international security [8], banking and finance [9], or network security [10].

Due to the aforementioned fact, there is a diverse number of techniques that contribute to the AI ecosystem. Next, a description of the main techniques is provided:

(a) Machine Learning (ML) [11]: ML is a mathematical model based on sample data, known as "training data" mainly used for data classification and data prediction without being explicitly programmed for doing so. That is, ML algorithms use computational methods to learn information from a set of data which is used for training the model. Once the model is trained, it can be used for classifying and predicting. There is a wide range of ML algorithms such as Random Forest (RF), Support Vector Machine (SVM), Decision Trees, and k-means.

(b) Deep Learning (DL) [12]: ML techniques are limited when natural data in the raw form needs to be processed. As a result of this, more complex methods such as DL have been developed. DL allows models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. In other words, a DL architecture is a multilayer stack of learning modules that compute non-linear input–output mappings. Each module transforms the input to increase the selectivity and the invariance of the representation that is expected to be classified.

(c) Neural Networks (NNs) [13]: Artificial NNs (ANNs), also called NNs, are computer systems inspired by biological NNs that constitute human brains. NNs are based on nodes that model neurons of a biological brain. These nodes are connected using synapses for transmitting information between them. NNs are also trained to perform tasks that are not explicitly programmed for doing.

(d) Natural Language Processing (NLP) [14]: The goal of NLP is twofold: (1) be able to communicate with humans and (2) to acquire information from written language. For doing so, an AI system needs to understand the language humans use by doing the following information-seeking tasks: text classification, information retrieval, and information extraction. Information retrieval is the task of obtaining information resources relevant to an information need, while information extraction is the task of automatically extracting structured information from machine-readable documents.

(e) Fuzzy approaches: Fuzzy logic was created to allow computers to mimic the way humans think [15]. In detail, fuzzy logic is a formal mathematical theory for the representation of uncertainty and extends Boolean logic using all the possible answers between 0 and 1 for reasoning and decision making. Unlike the probabilistic theory, fuzzy logic models the uncertainty of the definition of the event, and not the uncertainty if a certain event will happen or not. A common application of fuzzy logic is expert systems [16]. Expert systems are usually made up of at least two parts: an inference engine, which is the brain of the system and has the goal of obtaining relevant knowledge, understanding it, and finding an expert solution, and a knowledge base, where the knowledge of a certain domain is placed in the form of rules and facts. That is, a fuzzy expert system uses a collection of fuzzy membership functions and rules to reason about data.

(f) AI-based heuristics: Heuristics are methods of reasoning based only on partial evidence. This capacity is a typical human characteristic. The basis of heuristics is the experience in problem solving and learning. In computer science, heuristics are used for finding an optimal solution. AI-based heuristics comprise different methods and algorithms such as genetic algorithms (GAs) [17] or ant colony optimization (ACO) algorithms [18]. In short, GAs are search processes to find a solution for optimization and search problems inspired by evolutionary biology. On the other hand, ACO takes inspiration from the foraging behavior of some ant species.

It is expected that all these AI techniques will be the enablers of more sustainable, human-centric, and resilient PM and industry in general [1].

2.2. Emerging PM

The PM technology quotient (PMTQ) is a topic of ongoing debate in the PM community. PMTQ is defined as a person's ability to adapt, manage, and integrate technology based on the needs of the organization or the project. According to PMI [4], PMTQ is becoming more important as people and businesses seek digital sustainability. In addition, according to a survey of CEOs [4], 85 percent believe that "AI will significantly change the way they do business in the next five years". As a result, we anticipate that the PM community will incorporate AI techniques into PM methods in the near future.

Furthermore, with the emergence of new agile concepts and the need for projects to adapt to dynamic change, PMI [5] is considering practice-oriented PM with an emphasis on outcome and value delivery rather than processes and deliverables. In total, 12 principles are introduced by outcome-oriented methods for delivering values in projects. These principles define the what and why of managing projects. In addition, PMBOK7 describes the project performance system with a new approach by defining eight PDs. Project PDs include the stakeholder, team, development approach and life cycle, planning, work, delivery, measurement, and uncertainty. Following that, a description of the PDs is given:

(a) The stakeholder PD seeks a productive working relationship with stakeholders throughout the project. Identifying, understanding, analyzing, prioritizing, engaging, and monitoring the stakeholders are the steps of this PD;

(b) The team PD addresses activities and functions associated with the people who are responsible for producing project deliverables. Shared ownership, a high-performing team, and the demonstration of applicable leadership and other interpersonal skills by all project team members are outcomes to be measured in this PD;

(c) The development approach and life cycle PD determine whether the development strategy (predictive, hybrid, or adaptive) is appropriate for project and organizational variables and represents product features;

(d) The planning PD checks if the project progresses in an organized, coordinated, and deliberated manner; if there is a holistic approach to delivering the project outcomes; if evolving information is elaborated to produce the deliverables and outcomes; if time spent planning is suitable for the situation; and if the planning information is sufficient to manage stakeholder expectations and there is a process for the adaptation of plans throughout the project based on emerging and changing needs or conditions;

(e) The project work PD is associated with establishing project processes, fostering a learning environment, appropriate communication with stakeholders, efficient management of physical resources, effective management of procurement, and enhanced team capabilities due to continuous learning and process improvement;

(f) The delivery PD focuses on meeting requirements, scope, and quality expectations to produce the expected deliverables. It checks if projects contribute to business objectives and the advancement of strategy; if they realize the outcomes they were initiated to deliver; if the benefits are realized in the time frame in which they were planned; and if the team has a clear understanding of requirements and stakeholders accept and are satisfied with project deliverables;

(g) The measurement PD involves assessing project performance and implementing appropriate responses to maintain optimal performance. An effective measurement will result in a reliable understanding of the status of the project, actionable data to facilitate decision making, and appropriate actions to keep project performance on track;

(h) The uncertainty PD deals with activities and functions associated with risk and uncertainty. Suitable actions to address complexity, ambiguity, and volatility with robust systems for identifying, capturing, and responding to risk are included in this domain.

Emerging PM based on PDs and principals with demands concerning the integration of AI and PMTQ into PM, brings the need to study and understand how AI-enabled PM can be built.

3. Methodology

This study applies an SLR methodology based on a well-defined and well-planned protocol. Unlike the traditional literature review strategy in which the reviewer's subjectivity and informality can influence the outcome, the SLR method removes such prejudice by applying systematic procedures to identify, select, and evaluate a theme of interest [19]. This approach is particularly appropriate in this investigation due to its suitability to gather the most relevant research on emerging themes [20–22]. The review explores the use of AI in PM through a rigorous process that includes planning the search strategy, identifying targeted academic publications on established themes, determining inclusion and exclusion criteria, and conducting the review and reporting findings [19]. The SLR process was conducted in two phases. The first phase involves selecting keywords, establishing inclusion and exclusion criteria of papers for the study (i.e., published period, keywords, and language), and conducting the literature search. The second phase evaluates selected papers considering the latest standard of PMBOK7 principles and PDs.

The planning of the review process was focused on analyzing and understanding the nuances of the use of AI in the stages of PM in different domains. The authors brainstormed to establish the keywords and to define the review process's conceptual boundaries. At this point, it was predetermined that the papers published from 2011 to the present (April 2022) are the appropriate time range to focus on the publications on post declaration of the Industry 4.0 era. Authors reached a consensus over the combination of the keywords as "project management" AND "artificial intelligence". Two of the largest repositories of academic articles, Web of Science and Scopus, were chosen due to their higher scientific impact and thus to search for conforming peer-reviewed journals and conference papers [23]. The literature search was delimited exclusively to English language publications. The search for title, abstract, and keywords in selected databases was performed using search strings to ensure all the papers related to the use of AI in PM are selected.

The next level of the filtering process of the selected papers from the search process was first conducted by each author individually reviewing the articles and assessing them through screening criteria. The abstract and the conclusions of each selected article were thoroughly scrutinized at this stage. When either the authors are unsure as to whether the paper explicitly fits the study theme or concluded that the paper complies with the study criteria, the rest of the article was thoroughly read to ensure conformance to the research theme. Finally, the authors reassembled as a review panel to mutually determine the final sample of the SLR process that fits the conceptual boundary of the investigation. This compilation represents the most comprehensive body of academic work on AI in PM published to date to the best of the authors' knowledge.

Subsequently, we present the results of the SLR bibliometric analysis and the literature review categorized under the latest PMBOK7 PDs. Then, a discussion on the significant findings of the studied theme is conducted.

4. Results

4.1. Bibliometric Analysis

The Web of Science and Scopus literature searches in the first phase resulted in 79 and 722 hits, respectively. Later, in phase 2, once the articles found were evaluated, we finally identified 128 papers related to AI-enabled PM.

Figure 1 collects the bibliometric results of selected papers. The graph on the left shows an increasing interest in AI-assisted PM since the beginning of Industry 4.0, where the growing tendency for the last two-year period is still notable. The same plot illustrates that there are significantly more journal publications than conference papers in the AI–PM field. However, as depicted in the middle graph, the nature of the journals of the identified works is diverse and multi-disciplinary: they cover management (International Journal of Project Management is the most cited in that discipline), computer science (Expert Systems with Applications and Advances in Intelligent Systems and Computing journals remarkable), construction (Automation in Construction journal on the top), and engineering.

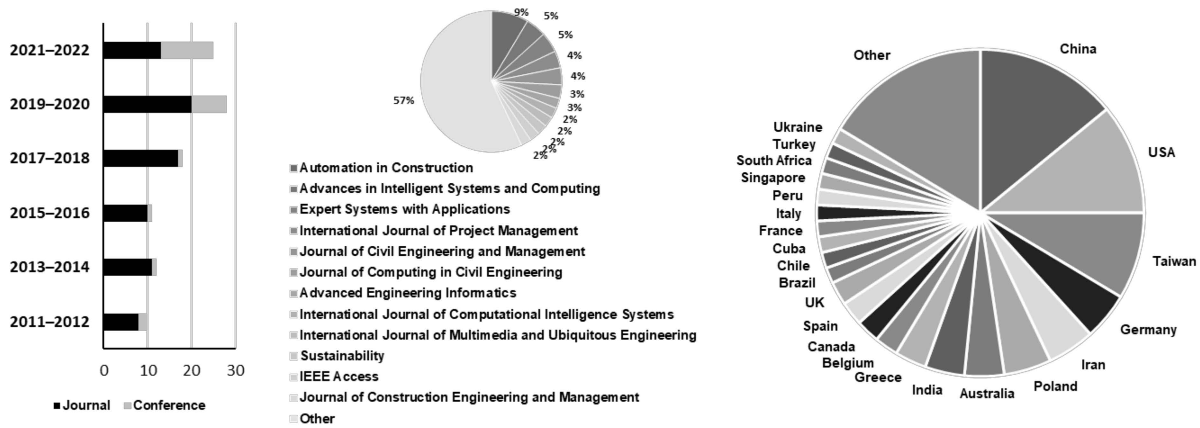

Figure 1. Bibliometric results. Temporal evolution with publication type (**left**), journals of selected papers (**middle**), and per-country distribution (**right**).

The right pie chart in Figure 1 provides the countries of the authors of the selected studies. As can be seen, China, the USA, and Taiwan lead the research, followed by different countries from different continents.

4.2. Literature Review

In this section, we report on the AI-assisted PM review based on the selected literature. First, we present the content classification of the identified investigations and then we conduct the literature review structured by PMPDs.

Figure 2 summarizes the content classification of the selected papers in different categories. In reference to the application sector (top-left plot), we found that almost half of the selected works focus on construction PM whereas the use of AI in IT projects is also pronounced (nearly 22%), while its application in other specific sectors (i.e., health) is too scarce. Moreover, AI-enabled approaches for generic PM are also remarkable.

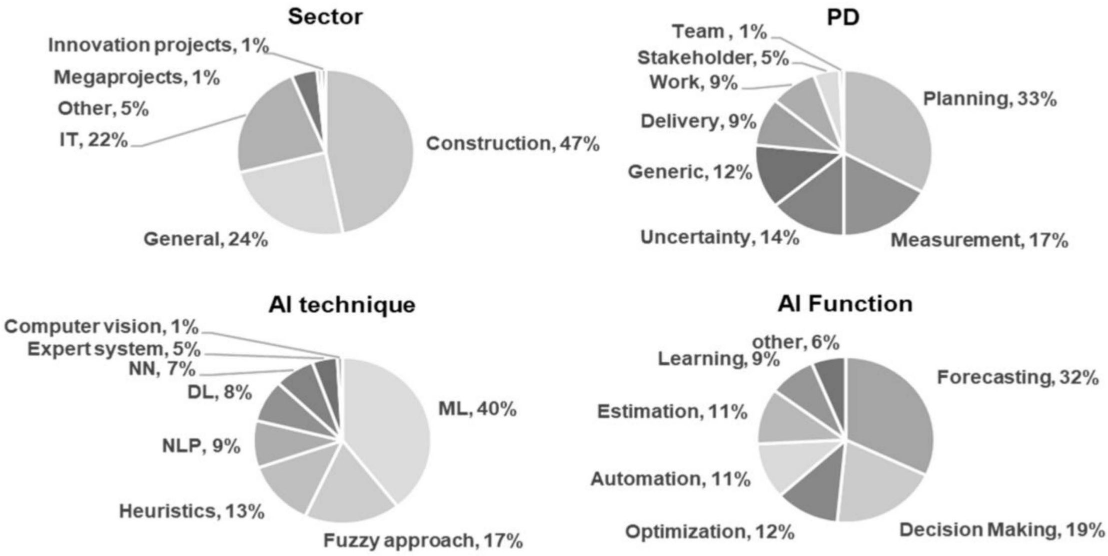

Figure 2. Content classification.

Concerning the classification of the existing literature in the PMPDs (depicted in Figure 2, top-right chart), we came to realize the fact that of the emphasis of papers is placed on planning PD; afterward, measurement and uncertainty PDs are importantly considered in the research. Moreover, the development approach and life cycle PD are quite neglectful in the studied topic.

Regarding AI techniques (Figure 2: down-left graph), ML is predominant, followed by fuzzy approaches, AI-based heuristics, and NLP. Furthermore, several works consider NN and DL to assist PM, while a few investigations include expert systems and computer vision. Moreover, in reference to AI functions, as shown in the down-right pie of Figure 2, the main one is AI-enabled forecasting in PM. Furthermore, the employment of AI methods for decision making is also relevant, coming after optimization, automation, and estimation. In addition, several studies deal with AI-based learning in PM.

4.2.1. Stakeholder PD

Mahfouz and Kandil [24] deal with ML-enabled litigation outcome prediction of differing site conditions. Their developed models are trained and tested using differing site condition cases, concluding that SVM performs the best. More recently, Zheng et al. [25] presented an ensemble ML model which combines gradient boosting decision tree, k-nearest neighbor, and NN techniques to forecast construction litigation outcomes in Public-Private Partnership (PPP) projects. The resulting accurate approach is trained and validated using data from China Judgements Online PPP litigation cases.

Moreover, Pérez Vera and Bermudez Peña [26] provided a fuzzy inference system to classify stakeholders using two ML clustering algorithms.

In addition, Guo et al. [27] proposed an interactive NLP-based solution to automate the visual design process with the product owner. An agent-based approach that uses NLP and efficient greedy-search heuristics for regulated design decision making in construction projects is provided in [28].

In another study, Miller [29] identified AI project success factors related to moral decision making. He claimed to be addressing the concerns and expectations of stakeholders in AI projects, with those factors being procedures for algorithm usage.

4.2.2. Team PD

For team communication, Hsu et al. [30] developed a feasible and effective ML-based system integrated in Building Information Modeling (BIM) for design clash resolution of construction projects, which is satisfactorily validated in the mechanical/electrical/plumbing systems of a student residence.

4.2.3. Development Approach and Life Cycle PD

There is no study specific to project development and life cycle PD.

4.2.4. Planning PD

Some studies focus on ML-based project duration prediction in project planning: Han et al. [31] compared different ML techniques to forecast software development time, concluding that the Gaussian process algorithm has the highest accuracy. An effective ensemble averaging of three ML algorithms (SVM, NN, and Generalized Linear Models) was introduced in [32] for software project duration estimation. the paper [33] estimated the duration of diaphragm wall construction using a fusion of the Least Squares SVM and the firefly algorithm, which achieved very low deviation prediction.

Moreover, the literature addresses AI-assisted scheduling issues in the construction sector: Faghihi et al. [34] reviewed the research on automation in construction scheduling, where different AI approaches are employed: case-based reasoning, knowledge-based techniques, GAs, expert systems, and NNs. They concluded that GAs are dominant. Moreover, Aljebory and QaisIssam [35] provided an automated project schedule planning framework that contains a knowledge-based expert system connected to Revid BIM and Primavera software. The developed AI-based scheduler retrieves construction design elements from BIM, and it provides the derived project activities and their sequencing on Primavera. The system validity was shown using a simple house building as a case study.

Furthermore, the use of AI techniques for the IT project scheduling problem was manifested in a few investigations [36–38]. Kucharska and Dudek-Dyduch [37] introduced an ML method for determining intelligent cooperation at IT project realization. The learning algorithm for a scheduling problem is presented with the results of computer experiments to prove its feasibility. A model for solving the software project scheduling problem using the firefly algorithm is provided in [36], which gives better results than GAs and ACO. In the work [38], ACO Extended and Max-Min Ant System heuristics were compared for the software project scheduling problem aimed at minimizing project duration. Findings revealed that ACO Extended is better than the Max-Min Ant System with respect to fitness value. Besides that, Hamada et al. [39] developed an NN estimation model to manipulate the timing problem for software projects. Their model predicts the estimation value of project time, which optimizes the scheduling process.

There are many studies related to AI-based software project effort estimation:

1. Fuzzy approaches: S.R. Sree and Ramesh [40] presented a model based on fuzzy logic. It was tested using the NASA93 dataset and concluded that the fuzzy model with triangular membership function outperforms the rest of the models. Furthermore, the authors in [41] provided a model by cascading fuzzy logic controllers, which improves the efficiency with clustering techniques. The NASA93 dataset was used as a case study, revealing that fuzzy models developed using subtractive clustering provide better results. Han et al. [42] presented an effective and accurate approach based on historical project data using the Gauss–Newton model to calibrate the parameters of the Constructive Cost Model and fuzzy logic to optimize it, thus Deming regression, expert judgment, and ML were also applied to enhance the model. González-Carrasco et al. [43] consider fuzzy input values in NN;
2. Methods based on ML or/and NN: The work [44] suggested a k-nearest neighbour ML-algorithm, concluding that the combination of k-nearest neighbour and quadratic regression has the best response, accuracy improvement, and relative error reduction. Nassif et al. [45] presented a comparative study of different NN models (multilayer

perceptron, general regression NN, radial basis function NN, and cascade correlation NN) and the International Software Benchmarking Standards Group dataset was used in the evaluation. The results showed that cascade correlation NN outperforms the other models. Different AI techniques (Artificial NN, GA, and fuzzy logic) were applied in [46] using data from past NASA projects, concluding that ANN methods give the best performance. An effective ML ensemble model composed of SVM, NN, and Generalized Linear Models is provided in [32]. In addition, Twala [47] investigated the effect of noisy domains on the learning accuracy of eight ML algorithms (SVM and ANN among them) and statistical pattern recognition algorithms. The study derived a solution from a probabilistic perspective that improves prediction for software effort corrupted by noise with better accuracy.

The assignment of human resources to project tasks that employ AI heuristics is another appearing topic in the literature [48–51]. The works [42] and [48] applied feasible ACO algorithms (improved Max-Min ACO and Hyper-Cube ACO, respectively) for worker-task assignment in software projects to minimize the project duration. The authors in [51] presented a novel ACO rescheduling strategy for human resource assignment to eliminate delays. Findings revealed that the new adaptative ACO outperforms common ACO and GAs. A tabu search algorithm was employed in [50] so as to solve the resource management problem for multi-unit construction projects. The case study analyzed manifested a reduction of 50% in the project execution time when using that algorithm.

Furthermore, aimed at allocating the suitable software developers for a particular project, Javeed et al. [52] proposed a DL-based approach to determine the software developer's coding expertise by analyzing prior written source code. Three DL methods were developed, trained, and evaluated in the study: Long Short-Term Memory (LSTM), one-dimensional convolutional NN, and a hybrid model that combines LSTM and the previous NN. Evaluation results indicate that LSTM outperforms the other two models, which achieves good accuracy levels.

Moreover, in the paper [53], evolutionary and hybrid evolutionary algorithms that are based on GA's principles are implemented for resource leveling in a ship construction project. Experimental results show that hybrid approaches provide slightly better behavior. Furthermore, a novel algorithm based on Sonar inspired optimization to address benchmark and resource-leveling problems was introduced in [54]. Evaluation findings revealed that it provides better performance than hybrid GAs. Koulinas and Anagnostopoulos [55] proposed a well-performing threshold-based hyperheuristic for solving construction resource levelling and allocation. In addition, Duraiswamy and Selvam [56] employed ACO in a metaheuristic approach to solve resource leveling problems. A real-time project was used to verify the efficiency of their model. The results were near-global optimum solutions.

Moreover, Amândio et al. [57] presented a planning optimization system using multi-objective GA, namely the NSGA-II, for road pavement rehabilitation. The model was able to choose the optimal allocation of heavy equipment with costs and duration objectives.

The study [58] demonstrates that SVMs and ANN ensemble techniques provide better results than single ANN models for predicting project costs. Well-performing models for construction cash flow forecasting were proposed in [59,60], which employ least squares SVM and a fuzzy SVM-GA ensemble, respectively. More recently, Cheng et al. [61] proposed an AI-based hybrid model, named symbiotic organisms search-optimized (SOS) NN LSTM, that accurately predicts the cash flow of construction projects; this novel DL-based model uses data from completed construction projects in Taipei.

Moreover, Wazirali et al. [62] focused on the way construction projects can minimize the building cost and materials wastages based on a GA-SVM inference system. Furthermore, a decision support model for dispatching construction machines was presented in [63], where a rule-based inference engine determines the most proper construction machine type considering both economic and technical criteria.

In addition, Li [64] proposed a method to combine AI middle office with Blockchain (BC) and BIM to analyze data when forecasting prices in construction projects.

Furthermore, the study [65] dealt with hybrid GA models to forecast bid award amounts for bridge construction projects. Several forecasting models (GA combinations with ANN, case-based reasoning, and regression-based approaches) were validated with data from public bridge construction projects in Taiwan, showing that ANNs in combination with GAs provide more reliable results.

Apart from that, an SVM procedure for bid/no bid decision making was presented in [66]; the method was evaluated in oil and gas platform fabrication projects, revealing that SVM outperforms Worth Evaluation Classifier, Linear Regression Classifier, and NN.

In another study, Ronghui and Liangrong [67] presented a fuzzy-based hybrid metaheuristic algorithm for establishinig the cost optimization of building materials in construction projects.

Moreover, Gerogiannis et al. [68] elaborated an approach for the selection of Project and Portfolio Management Information Systems which combines TOPSIS with intuitionistic fuzzy group decision making.

Once the problems related to the project planning phase through observation of IT development companies were determined, [69] proposed an AI-based framework that addresses the issues identified in order to enhance IT project planning. The proposal includes an expert system, whose knowledge base contains information on past projects, from which the inference engine will learn so as to predict planning outputs.

Furthermore, Kultin et al. [70] studied the ML approach for deciding whether to participate in a project tender. The built ML algorithms were tested with projects that applied for a tender, and the results indicated that the logistic regression algorithm used gives the most satisfactory performance.

Furthermore, Marchinares and Aguilar-Alonso [71] provided a brief literature review regarding the application of ML in PM, which concluded that ANN and SVM are the most used methods for software effort estimation, predicting project performance, and obtaining useful information from projects.

Moreover, two works have been found related to AI-based PM in an agile environment [72,73]. Hoa Khanh et al. [73] proposed a framework that integrates AI technologies to enhance several issues of agile PM; ML and DL techniques are suited for effort estimation, and ML-based analytics are suited for backlog item identification, backlog item refinement, and risk mitigation. What is more, DL-based NLP is considered to learn from and generate representations of project data that are computationally convenient to process. Furthermore, the literature review [72] showed the application of different AI techniques for BD analytics in agile software PM. According to the selected studies, the most popular AI methods used in such contexts are ML (dominated by SVM and RF-based ensemble models) and NNs with a few DL approaches; the key area for employing such techniques is software effort estimation.

4.2.5. Project Work PD

Authors in [74] developed a precise decision-making tool for contractor prequalification that includes a fuzzy expert system, while Hosny et al. [75] employed a fuzzy AHP approach for the same problem. What is more, SVM was used in [76] to reliably forecast a contractor's deviation from the client's objectives.

Moreover, Cirule and Berzisa [77] proposed a cost-effective AI-assisted chatbot framework for PM. The designed chatbot prototype was implemented using the Dialogflow Conversational platform, an agent for NLP, and in the following tool environments: Jira for project planning/tracking/management, Slack messaging platform for communication, Google Drive for project data storage, Google Calendar to schedule meetings, and Skype for users' communication. The proposed solution has the potential to save PM time and to reduce project failures.

Under the umbrella of the complexity of implementing and managing distributed information systems projects, Morozov et al. [78] proposed DL NNs for forecasting the state of the project when impacted by the changes caused by the environment. In this way, the developed AI model will help the effective proactive management of such complex IT projects, better ensuring their satisfactory performance.

The article [79] showed how it is possible to reuse knowledge intelligently in complex logistics projects through the integration of case-based and ontology-driven reasoning. More freshly, Jallow et al. [80] explored AI abilities to improve knowledge management for the construction industry; AI could be beneficial for future projects by gathering knowledge from past projects by automating data management. The research indicatd that UK firms have already implemented some sort of AI-based knowledge management within projects; combining AI systems into Common Data Environments can help project team members in finding and tracking documents efficiently.

Hajdasz [81] presented a decision support tool based on an expert system for flexible construction site management to develop optimal and attainable execution scenarios. It offers a dynamic construction process model that focuses on synchronizing resources and workflow continuity, which is crucial in scheduling and managing repetitive projects.

Furthermore, an ML-based tool for linking different documents from a project and having their traceability updated is provided in [82]. Moreover, Francois et al. [83] suggested a promising knowledge trace retrieval system for obtaining information from workers' emails based on ML techniques.

Allal-Cherif et al. [84] analyzed the five intelligent purchasing systems. The results suggested that AI makes purchasing missions more strategic and less operational, enhances the purchasing function, and strengthens the cross-functional role of purchasing.

4.2.6. Delivery PD

Some studies discuss AI-enabled compliance/conformance checking automation in construction projects: Salama and El-Gohary [85] introduced a deontic model with NLP for compliance checking; the work [86] proposed a ruled-based NLP approach for checking construction regulatory compliance documents, which wastested in quantitative requirements from 2009 International Building Code. J. Zhang and El-Gohary [87] provided compliance checking based on NLP and logic reasoning, which gave good detection and precision in a BIM case. An analysis of AI tools (text-process-data-image mining) for conformance checking was introduced in [88] and claimed that image processing still has performance gaps.

A few investigations show the application of AI for project quality management [89–91]. Badiru [89] used ANN in quality checking. Moreover, P. Zhou and El-Gohary [91] presented a well-performing ML-based text classification algorithm for classifying construction clauses in environmental regulatory documents. Moreover, Chiu [90] used a particle swarm optimization algorithm to search for suitable combinations among the software quality classification models, outperforming the independent software quality classification models.

Moreover, Dai et al. [92] suggested a decision support system based on vague grey matter elements and a fuzzy Analytical Hierarchy Process to evaluate university innovation projects, which provided six times the previous project evaluation information. Later, Fallahpour et al. [93] developed a fuzzy rule-based expert system for evaluating construction projects based on sustainability criteria using the fuzzy Analytical Hierarchy Process. It provides an Iranian construction company as a case study. Furthermore, the work [94] presented a model for classifying large-scale construction projects based on a sustainable success index that uses rough set theory for building a rule-based expert system.

Additionally, Perera et al. [95] developed a model for consolidating the critical success factors (CSF) of lean six sigma method. Their model proposed extracting the CSFs using a supervised DL–NN. This approach addresses the quality improvement language in projects and production.

4.2.7. Measurement PD

Several works dealt with AI-enabled project duration forecasting in Earned Value Management (EVM) context ([96–100]). Different ML algorithms, SVM in [100], k-nearest neighbor in [98], and others such as RF and decision tree in [99], were compared with the best performing EVM methods and it was concluded that AI techniques give better prediction than traditional EVM methods if the training and test sets are similar. Fasanghari et al. [96] suggested a fuzzy NN method (Locally Linear Neuro-fuzzy), whose accuracy, relevance, and applicability of the proposal were demonstrated via testing Iranian IT projects. The new ensemble learning model introduced in [97] was validated using data from real projects, showing that it notably outperforms well-known estimators.

Moreover, Yaseen et al. [101] proposed a robust and reliable tool that predicts delay levels in construction projects. For that aim, a hybrid AI model that combines GA with the RF-ML technique is employed, which is trained with data from past construction projects in Iraq.

Furthermore, Boejko et al. [102] suggested an original scatter search algorithm that applies the total weighted tardiness flow shop problem in construction PM, which considers technological and organizational restrictions; it produces better results than tabu search.

Apart from that, a tool for recognizing the activity of workers in construction projects was presented in [103]. When smartphone body movements are capturedML techniques can then be applied to determine the type of activity. What is more, Yang et al. [104] introduced a model that utilizes vision-based action recognition of construction workers using ML. SVMs are integrated with action learning classification, providing a notable accuracy enhancement with respect to other state-of-the-art solutions.

A case-based reasoning model to forecast the cost index of overhead transmission lines was provided in [105]. More recently, the study [106] introduced a new DL-based algorithm (LSTM NN) for highway construction cost index prediction, which provides precise forecasts in the short, medium, and long term. The model is trained with highway construction cost indexes from the Texas Department of Transport.

In addition, the works [96,100] also presented successful cost prediction in EVM, applying fuzzy NN and SVM, respectively. What is more, Mortaji et al. [107] used L-R fuzzy numbers to formulate EVM in vagueness environments for better planning, which provides efficient cost forecasting.

Moreover, the research in [108] developed a precise system that adopts DL with convolutional NN computer vision for the automatic remote monitoring of power substation construction management. Moreover, Cheng et al. [109] presented a hybrid AI model that accurately predicts the productivity of a construction project, which combines ML-based least square SVM, SOS, and feature selection techniques. Datasets from two Canadian past projects are utilized to build such a forecasting model. In addition, Umer et al. [110] suggested an emotion-based automatic ML approach to predict the priority of a bug report.

Moreover, several studies use AI techniques for the Project Monitoring and Controlling purpose:

Al-subhi et al. [111] applied an enhanced fuzzy cognitive maps approach for project monitoring that integrates diagnosis, decision, and prediction during project evaluation. The validation of the proposed model is performed by evaluating project records related to the PM knowledge areas of scheduling, cost, resource, quality, and procurement from the Research Database Repository of the University of Informatics Sciences of Cuba. Performance results indicated that the novel proposal outperforms fuzzy cognitive maps and neutrosophic cognitive maps techniques and experts expressed their satisfaction with the outcome obtained.

The article [112] introduced a system for construction PM that comprises AI together with Lean techniques and Enterprise Resource Planning, for improving productivity and minimizing resources in construction projects; it includes AI for project monitoring by analyzing worksite data with computer vision to predict the best continuity of construction activities in each scenario (e.g., doxel A which uses robots and drones with sensors to scan worksites and DL for production assessment and guarantee safety).

Teizer [113] presented an overview of computer vision-based sensing technology available for temporary resource tracking at infrastructure construction sites. It was concluded that robust and fast algorithms for long-term asset detection and tracking are a challenge to be addressed in future research. Furthermore, Yang et al. [114] reviewed computer vision-based construction performance monitoring methods, which include the visual monitoring of infrastructure/building, equipment, and workers. Studies ([113,114]) show the use of ML for the presented computer vision-based approaches.

The paper [115] analyzed the trends of computational intelligence techniques such as ML to be applied to project control.

Amer et al. [116] developed a method for the measurement of activities that automatically maps master schedule activities to planning tasks. Their NLP-based method uses a transformer, namely GPT-2, to automatically measure and map activities and tasks to one another.

Xiong et al. [117] proposed the use of 5G technology, combined with BD, AI, state perception, and video recognition technology to establish the 3D visualization platform of construction site information.

4.2.8. Uncertainty PD

Choetkiertikul et al. [118] provided an ML-based prediction system to forecast the risk of a task in a software project being delayed. Experimental results show that the collective classification method that this paper proposes significantly outperforms traditional approaches. Apart from that, the modeling of the probability distribution of project task duration by means of fuzzy expert estimates and fuzzy numbers is suggested in [119] which achieves more accurate estimations than existing methods under information uncertainty.

Okudan et al. [120] have designed and developed a well-performing project risk management tool that provides risk identification, analysis, response, and monitoring by means of an ML approach via cased based reasoning. Although it employs risk-related knowledge from past construction projects, it may be applicable in other sectors with minor changes.

Furthermore, the literature review paper [121] revealed the popularity of hybrid AI methods, such as fuzzy ANNs, fuzzy-analytical network processing, and fuzzy-simulation for risk assessment in construction projects. However, as stated in the previous study, a hybrid approach of fuzzy logic and an extended form of Bayesian belief network would better capture complexity-risk interdependencies under uncertainty moderating cost overruns.

Moreover, Poh et al., [122] provided an ML-based approach for developing leading indicators that classify sites in terms of their safety risk in construction projects. Five ML algorithms were used for training the sets (decision trees, RF, Logistics Regression, k-nearest neighbour, and SVM). Results show that RF gives the best prediction performance. In addition, an ACO model for planning a safe construction site layout that considers different safety objective functions was introduced in [123].

Moreover, the article [124] presented a stability prediction of construction projects based on ML algorithms. Furthermore, a framework based on fuzzy logic for digitalized PM was presented in [125]. It is applied for risk management in a railway project in Africa.

Furthermore, Chou et al. [126] introduced a fuzzy GA-based SVM model that gives accurate prediction of PPP dispute resolution outcomes in construction. Moreover, Chou et al. [127] proposed an optimized hybrid AI method that integrates a fast messy GA with an SVM to forecast dispute propensity in PPP construction projects; GA-SVM provides better prediction accuracy than other baseline models. Furthermore, Chaphalkar et al. [128] asserted the suitability of the multilayer perceptron NN approach for predicting the outcome of a dispute in construction projects using data from variation claims in India.

Moreover, Costantino et al. [129] provided an ANN-based decision support system to predict project performances for project selection, which relates critical success factors with project success by classifying the level of a project's riskiness via the experiences of project managers. Furthermore, the article [130] employs fuzzy decision making for project selection under uncertainty.

Di Giuda et al. [131] dealt with the application of AI-based NLP in PM, with a special focus on construction projects. In such a context, NLP, promising with an ANN approach, is proposed to efficiently extract knowledge from databases on construction accidents and translate it into useful data for safety risk management and also to predict risks in the bidding process of a project, by analyzing the uncertainty in the bidding document and extracting the influencing factors from it for bidding/tender risk forecasting.

In addition, the explorative study [132] presented some AI applications to manage megaprojects, most of them being related to the management of workers' safety and health. Predicting the presence of a disease, a risk condition, or the need for repairing heavy equipment are the benefits of ML applicable to megaprojects. Apart from that, employing NLP would help a project-based firm extract information regarding the perception of risk from hundreds of contracts.

Addionally, Choi et al. [133] developed a cloud-based integrated analysis tool using BD and ML technology to predict the risk of contractors and to support decision making at each project stage.

Moreover, Relich and Nielsen [134] presented a method for estimating the possibility of changes in production and warranty cost at the early stage of a new product design project. The method used a multilayer feedforward NN which is trained according to a gradient descent algorithm with momentum and adaptive learning rate backpropagation.

Indeed, Oliveira et al. [135] described the application of ML tools such as self-organizing maps and Bayesian networks in the reduction of uncertainties in project development time, better fit of the workforce to the type of project, reduction of reworks, and positively impacting on the final project costs.

4.2.9. Generic Investigations

By generic investigations we refer to those studies that deal with AI-based PM in a wider way (i.e., related to all knowledge areas or PDs in general, AI reviews and its adoption in PM, application in a sector, etc.); this research has been mainly established during the last two years.

In recent years, there has been a growing interest in exploring the potential of AI to revolutionize PM. Various scholars have conducted research to analyze the potential and limitations of AI in this field. Auth et al. [136] offered an overview of AI approaches and tools that can be employed for automating tasks in business project management. In another study, Auth et al. [137] presented a framework that defines the fundamental concepts for applying AI to PM, comprising both the requirements of AI application in PM as well as the requirements of PM from AI.

Furthermore, Bento et al. [138] carried out a systematic literature review to investigate the potentialities and limitations of AI in project management, highlighting an increased interest in the scientific community in this domain. Kuster [139] applied bibliometric analysis to the existing literature on AI in project management and identified emerging trends, including increased automation and data robustness in cost estimation models, intelligent project control systems based on earned value management, and optimization of input factors for effort estimation models.

Alshaikhi and Khayyat [140] examined the impact of AI on the future of PM and emphasized the importance of skilled project managers in contributing value to projects through their expertise. They also underscored the significance of possessing both manpower and AI skills to achieve successful project outcomes. Additionally, they suggested that project managers should concentrate on developing skills that AI cannot achieve to remain competitive in the industry.

Fridgeirsson et al. [141] presented survey-based research to explore the expected effect of AI on PM knowledge areas in the next 10 years. Findings reveal that project cost management, project schedule management, and project risk management are likely to be the most impacted by AI, especially in the planning phase for cost, risk, and schedule estimation. On the contrary, results indicated that knowledge areas and processes that require human skills will be the least affected by AI, highlighting the development and management of teams and stakeholder management. Additionally, the work in [142] provided a matrix method to develop purposeful AI use cases in the PM domain, where PM knowledge areas are in columns and AI functions (i.e., predicting and decision making) in rows; in this way, a specific problem related to a PM knowledge area that requires the human ability to be solved would be assigned to an AI function for being solved.

Moreover, the article [143] gave insights about the existing application of AI in PM and its future prospect. That work expresses that AI-based PM, along with the use of data collected from projects, improves PM processes and is commonly subjected to ML-based PM. Indeed, it is applied to schedule and cost prediction, assist in project tracking, determine project attributes by NLP, risk and resource management, and chatbots. Furthermore, the essay [144] is about the disruptive potential of AI, together with data analytics, in PM. As stated in that discussion, an AI-assisted PM will likely reduce repetitive PM tasks (such as estimating risks) and automate the tracking of communications among stakeholders. The author highlights that complex IT PM may particularly profit from AI, which may provide task completion estimation, effective task assignment, and advanced visualization techniques for tracing/tracking project processes.

Moreover, Ruiz et al. [145] reviewed a large number of AI learning techniques aimed at PM (e.g., NN, Fuzzy, etc.). The analysis is largely focused on hybrid systems and the results present different AI technique applications in the projects for the areas of tenders, human resources, IT, engineering and design, operations, supply chain, logistics, and construction.

In addition, Holzmann et al. [146] provided a visionary perspective study for the impact of AI on PM. A panel of 52 PM experts reflected on future potential AI applications for the PM Knowledge Areas. Based on a Delphi method, the study categorized relevant items in each of the PM Knowledge Areas. The most important functions to be supported by AI identified were to create a project schedule, analyze implications of missing deadlines, create a WBS/tasks list, create a project budget, update project progress and schedule, identify scope creep and deviations, produce a dynamic risk map, extract deliverables, prioritize tasks, and allocate team members.

Furthermore, Zhu et al. [147] pointed out 24 applications of cyber-physical systems, BD, AI, and smart robotics on project time, cost, and quality management, and found that the most influential applications of smart technologies are data collection for progress tracking, real-time monitoring, and schedule estimation.

Several recent studies focus on AI-assisted PM in the construction sector:

- Darko et al. [148] presented a scientometric study about the state-of-the-art of research on AI in the Architecture, Engineering, and Construction (AEC) industry. This work corroborated that the most often-used AI techniques in PM include GA, NNs, ML, and fuzzy logic and sets, becoming a trend convolutional NNs with DL (especially for damage detection). It was commented that cost, productivity, safety, and risk management were the mainstream issues in AI-assisted Architecture, Engineering, and Construction (AEC) research;
- By a literature search, [149] identified existing implementations that apply DL for construction PM in topics such as construction cost prediction, workforce activity assessment, construction site safety, and structural health monitoring and prediction. Future challenges in the application of DL include cash flow prediction, project risk analysis, and mitigation; DL-based voice chatbots integrated with BIM; and on-site safety and health monitoring by means of video feeds or even robots;
- Fayek [150] gave examples of applications of fuzzy hybrid techniques for construction PM: fuzzy ML combined with GA to predict labor productivity, fuzzy ML with fuzzy multicriteria decision making to identify the competencies that most significantly contribute to enhancement in project key performance indicators, fuzzy ML with fuzzy system dynamics to perform risk analysis, and fuzzy agent-based modeling to predict crew performance based on crew motivation levels;
- Makaula et al. [151] developed a framework for AI in construction management. A theoretical framework based on the research findings was developed which illustrates the application of AI technologies across the project lifecycle and the results of each application;

- Wu et al. [152] provided a state-of-the-art review appraising studies and applications of NLP in construction PM. They highlight that NLP is used to extract and exchange information and to support downstream applications.

Moreover, the editorial [153] provided an AI-enabled PM vision in the pharmaceutical research and development (R and D) context. Indeed, it predominately distributed AI-to-human operations in a lean and flexible manner and real-time accessibility and processing of project BD. While the pharmaceutical sector is in an early mature phase of employing AI, it is expected to use ML in order to enhance its R and D decision-making process before 2026. Furthermore, [154] dealt with how project managers in service industries use AI (referring to ML and DL) to support the PM process in the digital transformation era. For that purpose, interviews with service project managers from IT, aerospace, and construction were carried out, concluding that almost all project managers have a positive attitude towards AI adoption in their current or near future projects.

5. Discussion

This section gives observations on the contemporary state of AI-assisted PM based on the aforepresented literature review, followed by literature gap identification and recommendations for future investigation in such field.

Bibliometric results show a notable increasing number of high-impact publications related to the AI–PM topic during the last decade. According to the findings, construction is the most impacted sector by AI, which is due to the complexity of the megaproject nature of its projects. Selected studies propose different AI methods to assist different PM processes. The huge potential of AI is remarkably reflected in planning and measurement PDs, where a substantial amount of work has been dedicated to AI-enabled project time forecasting and software effort prediction. Furthermore, several investigations exist pertaining to AI-based uncertainty PD (which includes safety issues in construction), delivery PD (e.g., compliance/conformance checking automation in construction projects), and project work PD (e.g., forecasting the state of the project), while the literature encountered for the team and stakeholder PD are scarcer and diverse respect to AI functions.

Moreover, the collected research displays the evolution of AI technologies during the last decade. Under the predominance of ML, while in the initial period single methods are applied (e.g., a ML algorithm), ensemble and hybrid models that combine different algorithms and/or techniques aimed at improving the performance are utilized later (i.e., ML together with heuristics and fuzzy NN). Moreover, DL has become a trend in the last years, which gives solutions to more complex problems and enhances computer vision and NLP.

Furthermore, for the validation of the presented AI models project datasets of real projects are often used. Nevertheless, the literature reveals that AI application into real PM scenarios is still on an early stage.

We summarize the gaps identified in the literature referring to AI-based PM below:

Lack of a DL-based PM: While the literature has emphasised ML-enabled PM, DL is key for processing complex BD but it has been applied to a limited extent. Therefore, the potential of DL has not been fully considered in the digital PM.

Lack of AI-powered PM proposals in an agile environment: Despite the fact that a couple of studies discuss AI in agile PM, it is a topic that requires deeper investigation.

Lack of evidence of AI adoption for project managers: Although AI-enabled PM seems encouraging, its design, standardization, and implementation in project-based firms are still a challenge. Thus, AI adoption in PM is yet to be noted.

Lack of security issues of BD within the AI–PM ecosystem: The project BD used AI algorithms to assist PM is a major concern. Companies will be affected if data security, privacy, and authentication are not protected. However, we find that data security matters for AI-based BD analytics in the PM context are missing.

Lack of sustainability-aware AI-assisted PM: Industry 5.0, in line with the United Nations 2030 Agenda for Sustainable Development, highlights the inclusion of sustainability in emerging technology-enabled industries. Nonetheless, we have only identified two works in the AI–PM theme that take into account the sustainability criteria in project evaluation; hence, there is a hole in sustainable AI-based PM.

Considering the aforementioned gaps, we provide several recommendations for forthcoming research in the AI–PM field:

- Regarding AI as an enabler for project BD analytics, the future question is to what extent BD analytics requirements meet the promising features of cutting-edge AI, such as DL;
- Searching for comprehensive solutions to AI-powered agile PM remains a subsequent task;
- An AI-based PM approach will create an environment that will involve both project managers and IT people to work collaboratively to make disruptive AI technologies perform effectively. This builds a complex framework that demands the project manager's opinion on the adoption of AI in PM;
- Coming work needs to deal with security aspects in the AI–BD ecosystem within project-based firms;
- A study about the sustainable impact of AI-assisted PM will be desirable.

6. Conclusions

This study intends to comprehend how investigations on the application of AI in emerging PM can be categorized into PMPDs and which AI techniques have allowed PM to boost project performances with the intent of discovering solutions for the digital transformation towards Industry 5.0. According to the literature, AI techniques were developed to serve a variety of PDs in the construction, IT, and other industry sectors:

- Stakeholder management would use ML, NLP, and NN to understand, classify, and analyze stakeholders;
- AI-assisted communication in projects using ML demonstrates the potential to improve team performance;
- ML, NNs, GA, expert system, ACO, SVM-GA, and DL show promising usefulness for planning, duration prediction, effort estimation, scheduling, assignment of human resources to project tasks, resource leveling, and project cost estimation;
- In project work PD, the fuzzy expert system, SVM, NLP, DL, and NN can help with effective procurement management, appropriate communication with stakeholders, continuous learning, and the management of physical resources;
- The automation of requirements meetings and project quality management using DL, NN, and fuzzy bring the prospect of efficient project delivery;
- Using AI techniques (e.g., ML, SVM, GA, fuzzy, and NN) to measure project performance indexes, assess delays and implement appropriate responses, and monitor activities, gives rise to precise project measurement;
- AI-enabled uncertainty features address risk identification, probability distribution modelling, risk assessment, stability prediction, dispute risk forecasting, and project riskiness classification. AI techniques that improve for uncertainty functions include ML, fuzzy, ANN, ACO, and NLP.

Therefore, the given investigation contributes theoretically to PM digitalization literature by providing an understanding as to how AI could improve PMPDs. Practically, this research will make project managers aware of the potential of AI-enabled PM, encouraging investments on AI assisted PM in the digital transformation.

Nonetheless, there is a lack of investigation into the development of comprehensive frameworks for AI-based PM that take into account project life cycle PD, sustainability, security, and adoption by project managers, which remain future research tasks.

Indeed, the current study is limited to high-impact publications, so advances in AI–PM that have not been published are not covered; however, our findings provide a comprehensive understanding of the promise of AI for future PM.

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Abbreviations

ACO	Ant Colony Optimization
AEC	Architecture, Engineering, and Construction
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
ANN	Artificial Neural Network
BC	Blockchain
BD	Big Data
BIM	Building Information Modeling
CEO	Chief Executive Officer
CNN	Convolutional Neural Network
COVID-19	Coronavirus Disease 2019
CSF	Critical Success Factors
DL	Deep Learning
EVM	Earned Value Management
GAs	Genetic Algorithms
KNN	K-Nearest Neighbor
KPIs	Key Performance Indicators
LSTM	Long Short-Term Memory
ML	Machine Learning
NASA93	NASA93 dataset is a benchmark software defect dataset
NLP	Natural Language Processing
NNs	Neural Networks
NSGA-II	Non-dominated Sorting Genetic Algorithm II
PD	Performance Domain
PM	Project Management
PMBOK	Project Management Body of Knowledge
PMI	Project Management Institute
PMPDs	Project Management Performance Domains
PMTQ	PM Technology Quotient
PPP	Public-Private Partnership
R&D	Research and Development
RF	Random Forest
SLR	Systematic Literature Review
SOS	Symbiotic Organisms Search-optimized
SVM	Support Vector Machine
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
WBS	Work Breakdown Structure

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