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ESCUELA DE INGENIERÍA DE BILBAO

MÁSTER UNIVERSITARIO EN DIRECCIÓN DE PROYECTOS

TRABAJO FIN DE MÁSTER

AI-ENABLED PROJECT MANAGEMENT

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Abstract:

In the industry 5.0 era, industries are leveraging the potential of artificial intelligence in combination with innovative methods for more efficient production. In a similar approach, project management would benefit from Artificial Intelligence for achieving project goals by increasing in the project performances and consequently reaching a higher level of sustainability and success.

This thesis examines the role of artificial intelligence in project management. A systematic literature review of the applications of Artificial Intelligence techniques including machine Learning, deep learning, neural networks, natural language processing, fuzzy approaches and heuristics methods 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 results also indicate that artificial intelligence can play considerable role in the project management of construction, IT, and other industrial sectors and serve for improving planning, measurement and uncertainty with providing techniques for forecasting, decision making and optimization.

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

Laburpena:

5.0 industriaren garaian, industriak adimen artifizialaren potentziala aprobetxatzen ari dira ekoizpen eraginkorragoa lortzeko metodo berritzaileekin konbinatuta. Antzeko planteamendu batean, proiektuen kudeaketa AI-ari etekina aterako lioke proiektuaren helburuak lortzeko, proiektuaren errendimenduak handituz eta, ondorioz, arrakasta jasangarri handiagoa lortuz.

Tesi honek AI-ak proiektuen kudeaketan duen eginkizuna aztertzen du. AI tekniken aplikazioen azterketa sistematikoa aurkezten da, besteak beste, ikaskuntza automatikoa, ikaskuntza sakona, sare neuronalak, hizkuntza naturalaren prozesamendua, ikuspegi lausoak eta metodo heuristikoak proiektuen kudeaketaren errendimendu-domeinuetan. Emaitzek erakusten dute AI gaitutako PMri buruzko argitalpenen kopurua nabarmen handitu dela azken hamarkadan. Emaitzek ere adierazten dute IAk zeregin handia izan dezakeela eraikuntza, informatika eta beste industria-sektoreen proiektuen kudeaketan eta plangintza, neurketa eta ziurgabetasuna hobetzeko balio duela aurreikuspen, erabakiak hartzeko eta optimizatzeko teknikak eskainiz.

Gako-hitzak: adimen artifiziala; proiektu-kudeaketa; errendimendu-domeinuak; 5.0 industria.

Resumen:

En la era de la industria 5.0, las industrias están aprovechando el potencial de la inteligencia artificial en combinación con métodos innovadores para una producción más eficiente. En un enfoque similar, la gestión de proyectos se beneficiaría de la inteligencia artificial para lograr los objetivos de los proyectos, aumentando su rendimiento y, en consecuencia, alcanzando un mayor éxito sostenible.

Este tesis examina el papel de la inteligencia artificial en la gestión de proyectos. Se presenta una revisión bibliográfica sistemática de las aplicaciones de las técnicas de inteligencia artificial, incluyendo el aprendizaje automático, el aprendizaje profundo, las redes neuronales, el procesamiento del lenguaje natural, los enfoques difusos y los métodos heurísticos en los dominios de rendimiento de la gestión de proyectos. Los resultados muestran que el número de publicaciones influyentes sobre la gestión de proyectos con inteligencia artificial ha aumentado significativamente en la última década. Los resultados también indican que la inteligencia artificial puede desempeñar un papel considerable en la gestión de proyectos de la construcción, la informática y otros sectores industriales y servir para mejorar la planificación, la medición y la incertidumbre, proporcionando técnicas de previsión, toma de decisiones y optimización.

Palabras clave: inteligencia artificial; gestión de proyectos; dominios de rendimiento; Industria 5.0.

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1. Introduction

The worldwide COVID-19 pandemic has 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 "old normal" to "new normal" can be observed as an opportunity to reshape and renew the role of the industry in the society. In this context, the emerging Industry 5.0 concept has been released (Breque et al., 2021).

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). Further, 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. (2021) point out that AI is one of the enabling technologies that will help shifting 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 one researching on AI in 1947 (McCarthy, 1998). 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 COVID-19 pandemic for early detection and diagnosis of the patient and in the development of drugs and vaccines (Vaishya et al., 2020).

It is important to note that not only manufacturing processes will benefit from the application of new technologies, but business procedures like project management (PM) that are crucial in the daily operation of an organization, are also expected to take profit from them. In fact, cutting-edge PM trends focus on the use of AI at work. PMI (2019) 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 report mentions that project leaders say that AI technologies are encouraging

PM productivity and 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 domains (PMI, 2021). So, the question is how AI will be able to boost PM domains and procedures; and how is the literature developed in this theme?

Therefore, the goal of this thesis is to explore the role of AI in emerging PM. The thesis demonstrate a systematic literature review (SLR) of the application of AI technologies in PM performance domain (PD).

The rest of the thesis 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 result of bibliometric analysis and the literature review are developed and the findings are discussed, and, finally, in Section 5, the conclusions of the research 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 (Russel & Norvig, 2010): on the one hand, some researchers aim at introducing human minds' capacities into computers; while, 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 (Russel & Norvig, 2010), laid out along two dimensions: thinking (concerned with thought processes and reasoning) and acting (addresses behaviour). In addition, two different philosophies can be followed: a human-centred approach, that involves observations and hypotheses about human behaviour; or a rationalist approach, a combination of mathematics and engineering.

Thanks to its potential, AI can be used for innumerable purposes and fields like healthcare (Frazer et al., 2021), international security (Agarwala & Chaudhary, 2021), banking and finance (Warin & Stojkov, 2021) or network security (Thakkar & Lohiya, 2021). .

Due to the aforementioned fact, there is a diverse amount of techniques that build in the AI ecosystem. Next, a description of the main ones is provided:

a) Machine Learning (ML) (X.-D. Zhang, 2020): 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 or k-means.

b) Deep Learning (DL) (LeCun et al., 2015): ML techniques are limited when natural data in the raw form needs to be processed, e.g. transform pixel values of an image into data for a learning system, normally a classifier. Because 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) (Yegnanarayana, 2009): 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) (Chowdhury, 2003): The goal of NLP is twofold: (1) be able to communicate with humans; (2) acquire information from written language. For doing so, an AI system that wants to do knowledge acquisition 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 mimic the way humans think by L. Zadeh in 1965 (Zadeh, 1965). 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 are expert systems (Jackson, 1986). 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, understand it and find an expert solution; and a knowledge base, where the knowledge of a certain domain is placed in 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 base 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 like genetic algorithms (GAs) (Kumar et al., 2010) or ant colony optimization (ACO) algorithms (Dorigo, Birattari, & Stutzle, 2006). 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 behaviour of some ant species.

Table 1. summarizes the AI classifications, their respective techniques and the common purpose.

It is expected that all these AI techniques will be the enablers to a more sustainable, human-centric and resilient PM and industry in general (Breque et al., 2021).

Table 1- AI techniques classifications

Classification	ML	DL	NNs	NLP	Fuzzy	Heuristics
Techniques	Random Forest (RF) Support Vector Machine (SVM) Decision Trees k-means	non-linear input-output mappings	based on nodes that model neurons of a biological brain	text classification information retrieval information extraction	expert systems	Genetic algorithms (GAs) Ant Colony Optimization (ACO)
Purpose	Classifying and predicting	Classifying	Problem solving	communication with humans	Reasoning and Decision making	Reasoning, problem solving and learning, optimal solution

2.2. Emerging PM

On the one hand, PMI(2019) states that yet despite all the talk, project performance is not getting any better and emphasises on PM technology quotient (PMTQ) taking on a new urgency as people and companies search for digital sustainability. PMTQ is defined as person's ability to adapt, manage and integrate technology based on the needs of the organization or the project. On the other hand, 85 percent of respondents in a survey from CEOs (PMI, 2019) say AI "will significantly change the way they do business in the next five years." And close to two-thirds of global CEOs see it as a bigger disruptor than the Internet has been. Thus, the emerging PM will focus more on PMTQ and AI as skills for project managers and PM methods.

In this pathway and with the emerging of new agile concepts and the need to adapt to dynamic change, PMI (2021) is considering practice-oriented PM with focusing on the outcome and project delivery instead of processes and deliverables.

The outcome-focused methods for delivering values in projects empower 12 accepted principles for all industries and cultures. Those principles define the what and why of PM. Also, the project value delivery system with a new approach is designed in PMBOK7: the eight PDs of PM. These 8 PDs of PM seem to replace the 10 knowledge areas in the previous version of the standard. Project PDs are stakeholder, team, development approach and life cycle, planning, work, delivery, measurement and uncertainty. Following that, a description of the PDs is given:

The stakeholder PD seeks a productive working relationship with stakeholders throughout the project. Identifying, understanding, analysing, prioritising, engaging and monitoring the stakeholders are the steps of this PD.

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 demonstration of applicable leadership and other interpersonal skills by all project team members are outcomes to be measured in this PD.

The development approach and the life cycle of project are both important considerations. This PD determines whether the development strategy (predictive, hybrid, or adaptive) for deliverables represents product features and is appropriate in light of project and organizational variables.

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

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 improved team capabilities due to continuous learning and process improvement.

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

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.

The uncertainty PD addresses activities and functions associated with risk and uncertainty. Appropriate 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 on integration of AI and PMTQ into PM, brings the need to study on understanding how AI-enabled PM can be built.

3. Methodology

This study applies a SLR methodology based on a well-defined and well-planned protocol. Unlike the traditional literature review strategy that the reviewer's subjectivity and informality can influence the outcome, the SLR method removes such prejudice through applying systematic procedures to identify, select and evaluate a theme of interest (Tranfield et al., 2003). This approach is particularly appropriate in this investigation due to its suitability to gather the most relevant research on emerging themes (Aarseth, et al., 2017; Borges, et al., 2020; Taboada & Shee, 2020).

The review explores the use of AI in PM through a rigorous process that includes planning search strategy, identifying targeted academic publications on established themes, determining inclusion and exclusion criteria, conducting the review and reporting findings (Tranfield et al., 2003). The SLR process was done 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.

Planning of the review process was focused on analysing and understanding the nuances of the use of AI in PM in different PDs.

It was brainstormed with the help of PM and AI experts 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.

A consensus over the combination of keywords as "project management" AND "artificial intelligence" was reached. Two of the largest repositories of academic articles, Web of Science and Scopus, were chosen due to their higher scientific impact to search for conforming peer-reviewed journal and conference papers (Martín-Martín et al., 2018). 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 done through 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 there is not enough confidence that if 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 the conformance to the research theme.

Finally, a review panel is reassembled as to mutually determine the final sample of the SLR process that fits the conceptual boundary of the investigation. This compilation represents a 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 significant findings of the studied theme is conducted.

4. Results

4.1. Bibliometric Analysis

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

Figure 1 collects bibliometric results of selected papers. The graph shows an increasing interest in AI-assisted PM since the beginning of Industry 4.0, where the growing tendency for the last two-years period is still notable. The same plot illustrates that there are significantly more journal publications than conference papers in AI-PM field.

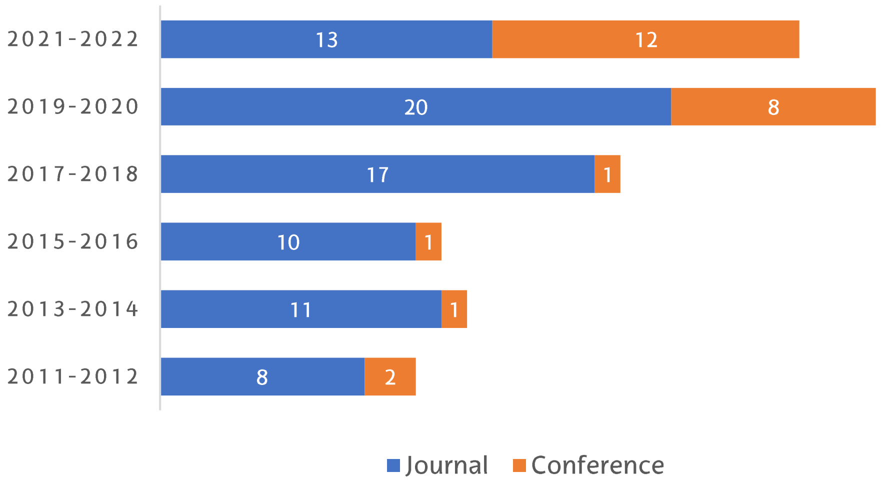

Figure 1- Bibliometric results: evolution with publication type

However, as depicted in Figure 2, the nature of the journals of the identified works is diverse and multi-disciplinary; they cover management (International Journal of Project Management the most cited in that discipline), computer science (Advances in intelligent systems and computing, Expert Systems with Applications journal remarkable), construction (Automation in Construction journal on the top) and engineering.

Besides, the Figure 3 provides the countries of the authors of the selected studies. As can be seen, China, USA and Taiwan lead the research, followed by different countries from different continents.

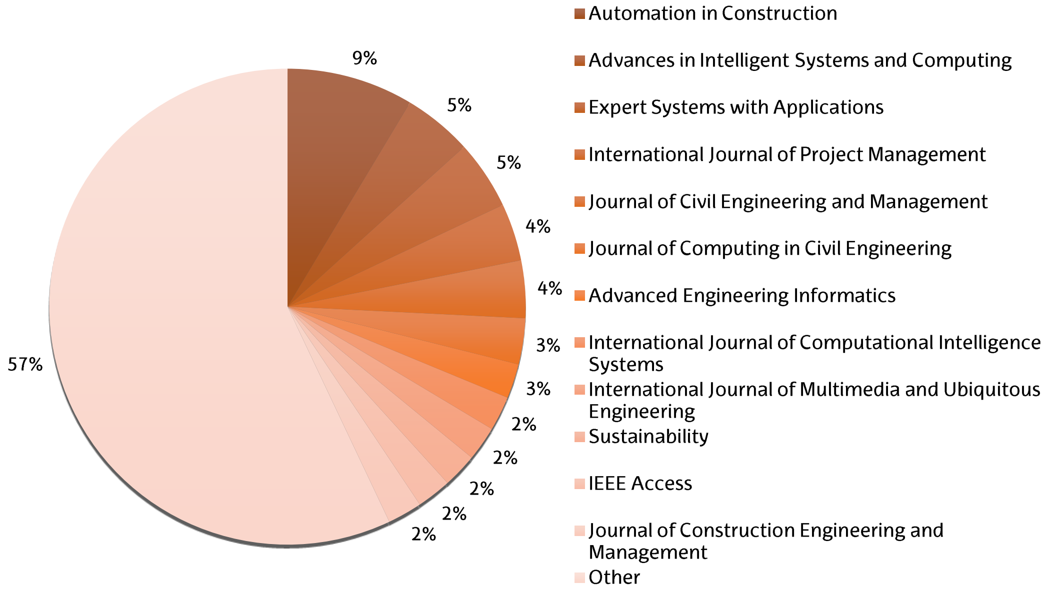

Figure 2- Bibliometric results: journals

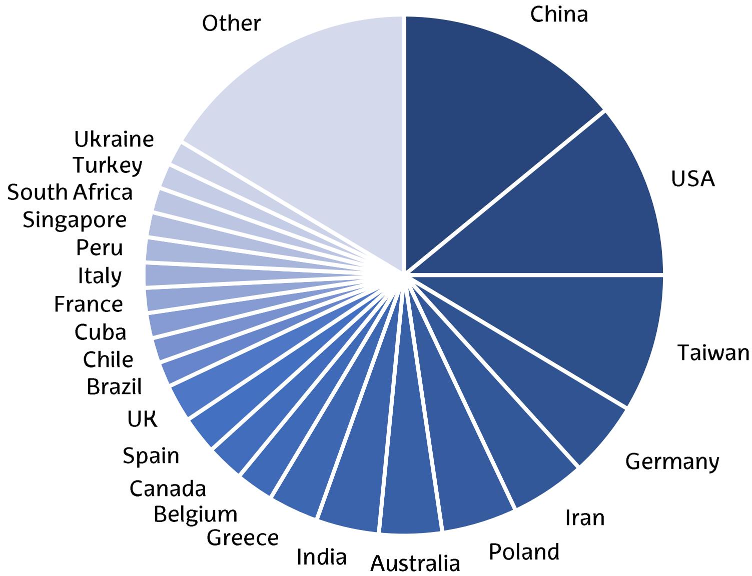

Figure 3- Bibliometric results: country distribution

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

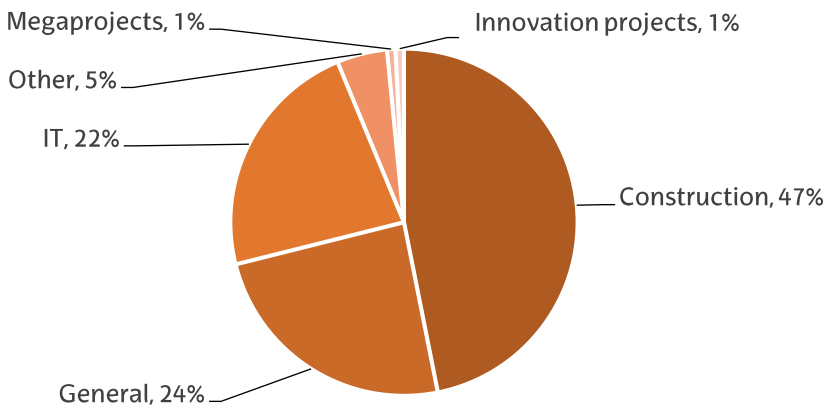

Figure 4- Findings classification by Sector

Concerning the classification of the existing literature in the PMPDs (depicted in Figure 5), we found that the one third of selected works are in the domain of Planning, while Measurement (near 17%) and Uncertainty (around 12%) are considered in other works. Moreover development approach and life cycle PD has not considered in the works.

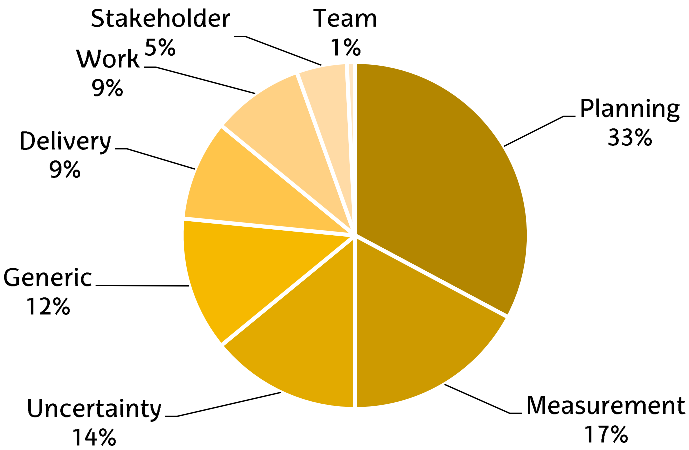

Figure 5- Findings classification by PD

Regarding AI techniques (Figure 6), 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.

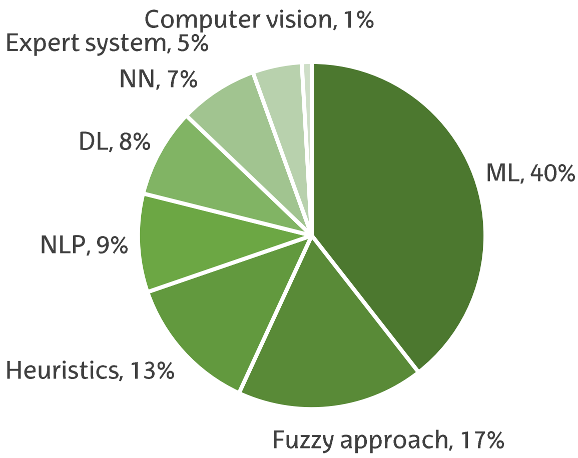

Figure 6- Findings classification by AI techniques

Besides, in reference to AI functions, as shown in Figure 7, the main one is AI-enabled forecasting in PM. Further, 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.

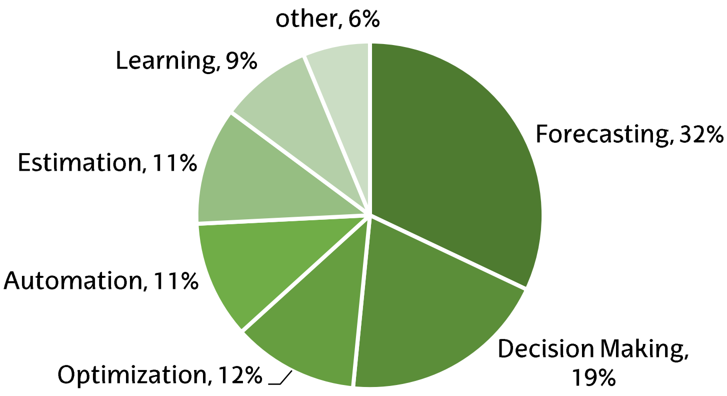

Figure 7- Findings classification by AI function

In the next sections, details of techniques that are found in the literature for each PD is described. The aim is to illustrate the related works under the same discussion title and provide a comprehensive summary of works for related subjects.

4.2.1. Stakeholder PD

Mahfouz and Kandil (2012) deal with ML-enabled litigation outcome prediction of differing construction site condition; developed models are trained and tested using differing site condition cases, concluding that SVM performs the best.

More recently, Zheng et al.(2021) present an ensemble ML model – which combines gradient boosting decision tree, k-nearest neighbour and NN – to forecast construction litigation outcome in Public-Private Partnership (PPP) projects. The resultant accurate approach is trained and validated using data from PPP litigation cases from China Judgements Online database.

Besides, Pérez Vera and Bermudez Peña (2018) provide a fuzzy inference system to classify stakeholders using two ML clustering algorithms.

Also, Guo et al. (2020) propose an interactive NLP-based solution to automate visual design process with product owner; an agent-based approach that uses NLP and an efficient greedy-search heuristics for regulated design decision-making in construction projects is provided in (Karan et al., 2020).

In another study, Miller (2021) identify 71 AI project success factors in 14 groups related to moral decision-making with algorithms. He claims that those factors are procedures for the usages of the algorithms to addressing the concerns and expectations of the stakeholders in AI projects.

Table 2 summarizes the AI techniques for the stakeholder PD : for the purpose of classifying stakeholders, fuzzy approaches is practically helps PM. Also NLP can be used for engaging stakeholders purposes and ML techniques have shown applicability in litigation purposes.

Table 2- AI-enabled Stakeholder PD

Purpose	AI technique	Reference
litigation outcome prediction	**SVM, ML**	Mahfouz and Kandil (2012) Zheng et al.(2021)
Classify stakeholders	**Fuzzy**	Pérez Vera and Bermudez Peña (2018)
Engage Stakeholders	**NLP**	Guo et al. (2020) (Karan et al., 2020)
Moral decision-making	**Algorithms**	Miller (2021)

4.2.2. Team PD

We found one paper about AI-assisted communication in project design: the work presented in (Hsu et al., 2020) develops 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 mechanical/electrical/plumbing systems of a student residence.

Table 3 summarizes the AI techniques for the Team PD. There are no so many papers found for the AI techniques for Team performance management. ML has the capability to increase the team communication performance.

Table 3- AI-enabled Team PD

Purpose	AI technique	Reference
Team Communication	ML	(Hsu et al., 2020)

4.2.3. Development Approach and Life Cycle PD

No studies have been found specific to project development and life cycle PD. While some AI techniques for decision making seem to be helpful for selecting the development approach and enhance the life cycle of projects, but in our research such studies are not identified.

4.2.4. Planning PD

Some studies focus on ML-based project duration prediction in project planning phase: Han et al.(2015b) compare 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) has been introduced in (Pospieszny et al., 2018) for software project duration estimation; the paper (Cheng & Hoang, 2018) estimates the duration of diaphragm wall construction using a fusion of the Least Squares SVM and the firefly algorithm, which achieves very low deviation prediction.

Moreover, the literature addresses other AI-assisted scheduling issues in the construction sector:

Faghihi et al. (2015) review the research on automation in construction scheduling, where different AI approaches are employed: case-based reasoning, knowledge-based techniques, GAs, expert systems, and NNs; it concludes that GAs are dominant.

Aljebory and QaisIssam (2019) provide 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 is shown using a simple house building as case study.

Further, the use of AI techniques for the IT project scheduling problem is manifested in a few investigations (Crawford et al., 2016; Kucharska & Dudek-Dyduch, 2014; Rachman & Ma'sum, 2018). Kucharska and Dudek-Dyduch (2014) introduce a ML method for determining intelligent co-operation at IT project realization. The learning algorithm for a scheduling problem is presented with results of computer experiments to prove its feasibility. A model for solving the software project scheduling problem using firefly algorithm is provided in (Crawford et al., 2016), which gives better results than GAs and ACO. In the work

(Rachman & Ma'sum, 2018) ACO Extended and Max-Min Ant System heuristics are compared for the software project scheduling problem aimed at minimizing project duration. Findings reveal that ACO Extended is better than Max-Min Ant System with respect to fitness value. Beside that, Hamada et al. (2021) aim to develop a NN estimation model to manipulate the problem of timing for software projects. Their model can predict the estimation value of project time, which optimizes the scheduling process and the developed model achieves high accuracy after testing.

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

- Fuzzy approaches: S. R. Sree and S. N. S. V. S. C. Ramesh (2016) present a model based on fuzzy logic; it is tested using the NASA93 dataset, concluding that the fuzzy model with triangular membership function outperforms the rest of the models. Further, the authors in (P. R. Sree & S. N. S. V. S. C. Ramesh, 2016) provide a model by cascading fuzzy logic controllers, which improves the efficiency with clustering techniques. The NASA93 dataset is used as a case study, revealing that fuzzy models developed using subtractive clustering provide better results. Han et al.(2015a) present 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; deming regression, expert judgment and ML are also applied to enhance the model. González-Carrasco et al. (2012) consider fuzzy input values in NN.
- Methods based on ML or/and NN: The work (Soltanveis & Alizadeh, 2016) suggests 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.(2016) present a comparative study of different NN models (multilayer perceptron, general regression NN, radial basis function NN and cascade correlation NN); the International Software Benchmarking Standards Group (ISBSG) dataset is used in the evaluation, and results show that cascade correlation NN outperforms the other models. Different AI techniques (Artificial NN, GA and fuzzy logic) are applied in (Abulalqader & Ali, 2018) using data from past NASA projects, concluding that

ANN methods give the best performance. An effective ML ensemble model – composed by SVM, NN and Generalized Linear Models – is provided in (Pospieszny et al., 2018). In addition, Twala (2014) investigates 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 derives 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 employs AI heuristics is another appearing topic in the literature (Crawford et al., 2015; Han, et al., 2015a; Podolski, 2017; W. Zhang et al., 2018). The works (Han et al., 2015b) and (Crawford et al., 2015) apply feasible ACO algorithms (improved Max-Min ACO and Hyper-Cube ACO respectively) for worker-task assignment in software projects to minimize the project duration and its overall cost. The authors in (W. Zhang et al., 2018) present a novel ACO rescheduling strategy for human resource assignment to eliminate delays. Findings reveal that the new adaptative ACO outperforms common ACO and GAs. A tabu search algorithm is employed in (Podolski, 2017) so as to solve the resource management problem for multiunit construction projects. The case study analysed manifests 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.(2020) propose a DL-based approach to determine software developer's coding expertise by analysing prior written source code. Three DL methods were developed, trained and evaluated in the study: Long Short-Term memo (LSTM), one-dimensional convolutional NN and a hybrid model that combines LSTM and the previous NN. Evaluation results indicate that LSTM gives the best performance in comparison to the other two models, which achieves good accuracy levels.

Moreover, in the paper (Gaitanidis et al.,2016) evolutionary and hybrid evolutionary algorithms that are based on GA's principles are implemented for resource levelling in a ship construction project. Experimental results show that hybrid approaches provide slightly better behaviour. Further, a novel algorithm based on Sonar inspired optimization to address benchmark and resource-levelling problems is introduced in (Tzanetos et al., 2018). Evaluation findings reveal that it provides better performance than hybrid GAs. Koulinas and Anagnostopoulos (2012) propose a well-performing threshold-based hyperheuristic for solving construction resource levelling and allocation.(Planning) Recently, Duraiswamy and Selvam (2022) utilized ACO in a metaheuristic approach to solve resource levelling problems,. A real-time project is used to verify the efficiency of the proposed model. The results obtained from the ACO model are near-global optimum solutions that eliminate premature convergence.

In other researches, Amândio et al.(2021) present an optimization system using multi-objective GA, namely the NSGA-II for road pavement rehabilitation PM that is able to choose the optimal allocation for heavy equipment in function of objectives such as construction costs and duration. The study (Wang et al., 2012) demonstrates that SVMs and ANN ensemble techniques provide better results than single ANN models for predicting project cost success. Well-performing models for construction cash flow forecasting are proposed in (Cheng et al. 2015; Cheng & Roy, 2011), which employ least squares SVM and a fuzzy SVM-GA ensemble respectively. More recently, Cheng et al.(2020) propose 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.

Besides, Wazirali et al.(2014) focus on the way construction projects can minimize the cost of building and wastages of materials based on a GA-SVM inference system. Further, a decision support model for dispatching construction machines is presented in (Xing et al.,2016), where a rule-based inference engine determines the most proper construction machine type considering both economic and technical criteria.

Furthermore, the study (Chou et al., 2015) deals with hybrid GAs models to forecast bid award amounts for bridge construction projects. Several forecasting models (GA combinations with ANN, case-based reasoning and regression-based approaches) are validated with data from public bridge construction projects from the Taiwan government e-procurement system, showing that ANNs in combination with GAs provide more reliable results.

Apart from that, a SVM procedure for bid/no bid decision making is presented in (Sonmez & Sözgen, 2017); the method is evaluated in oil and gas platform projects, revealing that SVM outperforms Worth Evaluation Classifier, Linear Regression Classifier and NN.

Also Li et al. (2021) propose a method to combine AI middle office with Blockchain (BC), and BIM to analyse data when forecasting prices in construction projects.

In another study, Ronghui and Liangrong (2021) present an intelligent fuzzy-based hybrid metaheuristic algorithm for analysis the strength, energy and cost optimization of building material in construction management.

Moreover, Gerogiannis et al.(2011) elaborate an approach for the selection of Project and Portfolio Management Information Systems which combines TOPSIS with intuitionistic fuzzy group decision making.

Once determined problems related to the project planning phase through observation on IT development companies, (Hassani & El Bouzekri El Idrissi, 2019) proposes 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 of past projects, from which the inference engine will learn so as to predict planning outputs.

Kultin et al.(2020) study the ML approach to decide to participate in a project tender. The built ML algorithms were tested with projects that applied for a tender, and results indicate that the logistic regression algorithm used gives the most satisfactory performance.

Further, Marchinares and Aguilar-Alonso (2020) provide a brief literature review regarding the application of ML in PM, which concludes that ANN and SVM are the most used methods for software effort estimation, predicting project performance and obtaining useful information from projects.

Besides, two works have been found related to AI-based PM in agile environment

(Biesialska et al., 2021; Hoa Khanh et al., 2019). Hoa Khanh et al. (2019) propose 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 for backlog item identification, backlog item refinement and risk mitigation. What is more, DL-based NLP is considered to learn and generate representations of project data that are computationally convenient to process. Furthermore, the literature review (Biesialska et al., 2021) shows 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 context 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.

Table 4 summarizes the AI techniques for the planning PD.

Table 4- AI-enabled Planning PD

Purpose	AI technique	Reference
Project duration prediction	**ML**	Han et al.(2015b) Pospieszny et al. (2018) Cheng & Hoang, 2018
Scheduling in Construction Sector	**GA** **expert system**	Faghihi et al. (2015) Aljebory and QaisIssam (2019)
Scheduling in IT sector	**ML** **Firefly algorithm** **ACO** **NN**	Crawford et al.(2016) Kucharska & Dudek-Dyduch (2014) Rachman & Ma'sum (2018) Hamada et al. (2021)
Effort estimation	**Fuzzy approaches** **ML** **NN**	S. R. Sree and S. N. S. V. S. C. Ramesh (2016) Han et al.(2015a) González-Carrasco et al. (2012) Soltanveis & Alizadeh (2016) Nassif et al.(2016) Abulalqader & Ali (2018) Twala (2014) Aguilar-Alonso (2020)
Assignment of human resources to project tasks	**ACO** **DL** **NN**	Crawford et al.(2015) Han, et al. (2015a) Podolski (2017) W. Zhang et al. (2018) Javeed et al.(2020)
Resource Leveling	**GA** **ACO**	Gaitanidis et al.(2016) Tzanetos et al. (2018) Koulinas and Anagnostopoulos (2012) Duraiswamy and Selvam (2022) Amândio et al.(2021)
Cost Estimation, Cash Flow estimation	**SVM** **NN** **GA**	Wang et al. (2012) Cheng et al.(2015) Cheng & Roy(2011)

	Fuzzy approaches	Cheng et al.(2020) Wazirali et al.(2014) Xing et al.(2016) Chou et al. (2015) Li et al. (2021) Sonmez & Sözgen (2017) Ronghui and Liangrong (2021)
Project planning	**Expert system** **Fuzzy approaches** **ML**	Hassani & El Bouzekri El Idrissi (2019) Gerogiannis et al.(2011) Kultin et al.(2020)
Agile projects planning	**ML** **DL** **NN** **NLP**	Hoa Khanh et al. (2019) Biesialska et al.(2021)

4.2.5. Project Work PD

Authors in (Awad & Fayek, 2012) develop a precise decision-making tool for contractor prequalification that includes a fuzzy expert system, while Hosny et al.(2013) employ a fuzzy AHP approach for the same problem. What is more, SVM is used in (Movahedian Attar et al., 2013) to reliably forecast a contractor's deviation from client's objectives.

Besides, Cirule and Berzisa (2019) propose a simple and cost-effective AI-assisted chatbot framework for PM. The designed chatbot prototype has been implemented using the Dialogflow Conversational platform, an agent for NLP, and in the following tool environment: Jira for project planning/tracking/management, and Slack messaging platform for users' communication; Google Drive for project data storage, Google Calendar to schedule meetings with project stakeholders, 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. (2020) propose 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 to the effective proactive management of such complex IT projects, better ensuring their satisfactory performance.

The article (Kowalski et al., 2012) shows 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.(2020) explore about AI abilities to improve knowledge management for the construction industry; AI could be beneficial for future projects through gathering knowledge from past projects by automating data management. The research manifests 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.

Further, a ML-based tool for linking different documents from a project and having their traceability updated is provided in (Mills et al., 2018). Moreover, Francois et al.(2016) suggest a promising knowledge trace retrieval system for obtaining information from workers emails based on ML techniques.

Hajdasz (2014) presents 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.

Allal-Cherif et al.(2021) analyse the five intelligent purchasing systems. The results suggest that AI makes purchasing missions more strategic and less operational, enhances the purchasing function and strengthens the cross-functional role of purchasing. Allal-Cherif et al.(2021) highlight that the adoption of AI is subject to certain limitations, and its power must not be overestimated.

Table 5 shows a summary on the AI techniques for the project work PD.

Table 5- AI-enabled project work PD

Purpose	AI technique	Reference
Contractor prequalification	**Fuzzy approaches** **SVM**	Awad & Fayek (2012) Hosny et al.(2013) Movahedian Attar et al. (2013)
Project Communication	**NLP**	Cirule and Berzisa (2019)
Change Management	**DL** **NN**	Morozov et al. (2020)
Knowledge Management	**ML**	Kowalski et al.(2012) Jallow et al.(2020) Mills et al. (2018) Francois et al.(2016)
Managing physical resources	**Expert system**	Hajdasz (2014)
Working with procurements	**AI in general**	Allal-Cherif et al.(2021)

4.2.6. Delivery PD

Some studies exist about AI-enabled compliance/conformance checking automation in construction projects: Salama and El-Gohary (2013) introduce a deontic model with NLP for compliance checking; the work (Jiansong Zhang & El-Gohary, 2016) proposes a ruled-based NLP approach for checking construction regulatory compliance documents, which is tested in quantitative requirements from 2009 International Building Code; J. Zhang and El-Gohary (2017) provide compliance checking based on NLP and logic reasoning, which gives good detection and precision in a BIM case; an analysis of AI tools (text-process-data-image mining) for conformance checking is introduced in (Kang & Haas, 2018), claiming that image processing still has performance gaps.

A few investigations show the application of AI for project quality management (Badiru, 2018; Chou et al., 2015; P. Zhou & El-Gohary, 2016). Badiru (2018) uses ANN in quality checking.

Besides, P. Zhou and El-Gohary (2016) present a well-performing ML-based text classification algorithm for classifying construction clauses in environmental regulatory documents. Moreover, Chiu (2011) uses a particle swarm optimization algorithm to search for suitable combinations among the software quality classification models, outperforming the independent software quality classification models.

Moreever, Dai et al.,(2016) suggest a decision support system based on vague grey matter element and fuzzy Analytical Hierarchy Process to evaluate university innovation projects, which provides six times previous project evaluation information. Later, Fallahpour et al. (2020) develop a fuzzy rule-based expert system for evaluating construction projects based on sustainability criteria using fuzzy Analytical Hierarchy Process; it provides an Iranian construction company as a case study. Furthermore, the work (Akbari et al. 2018) presents 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.

Perera et al. (2022) attempt to develop a model for consolidating the critical success factors (CSF) of lean six sigma method. Their model propose extracting the CSFs using a supervised DL-NN. This novel approach addresses the challenges associated with the unique characteristics of the quality improvement language in projects and production. Table 6 shows a summary on the AI techniques for the delivery PD.

Table 6-AI-enabled Delivery PD

Purpose	AI technique	Reference
Compliance/conformance automation	**NLP** **DL** **ML**	Salama and El-Gohary (2013) Jiansong Zhang & El-Gohary (2016) J. Zhang and El-Gohary (2017) Kang & Haas, 2018 El-Gohary (2016)
Quality management	**NN**	Badiru (2018) Chou et al. (2015); P. Zhou & El-Gohary (2016) Chiu (2011) Perera et al. (2022)
Requirement management	**Fuzzy approaches**	Dai et al.(2016) Fallahpour et al.(2020) Akbari et al. (2018)

4.2.7. Measurement PD

Several works deal with AI-enabled project duration forecasting in Earned Value Management (EVM) context (Fasanghari et al., 2015; Hajiali et al., 2020; Wauters & Vanhoucke, 2014, 2016, 2017). Different ML algorithms, SVM in (Wauters & Vanhoucke, 2014), k-nearest neighbour in (Wauters & Vanhoucke, 2017) and others such as RF and decision tree in (Wauters & Vanhoucke, 2016), are compared with the best performing EVM methods, concluding that AI techniques give better prediction than traditional EVM methods if the training and test sets are similar. Fasanghari et al. (2015) suggest a fuzzy NN method (Locally Linear Neuro-fuzzy), whose accuracy, relevance and applicability of the proposal are demonstrated via testing Iranian IT projects. The new ensemble learning model introduced in (Hajiali et al., 2020) is validated using data from real projects, showing that it notably outperforms well-known estimators.

Moreover, Yaseen et al.(2020) propose a robust and reliable tool that predicts delay levels in construction projects based on delay risk sources. 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.(2012) suggest 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 is presented in (Akhavian & Behzadan, 2016). With smartphones body movements are captured, and, then, ML techniques are applied to determine the type of activity. What is more, Yang et al.(2016) introduce a model that utilizes vision-based action recognitions of construction workers using ML. SVMs are integrated with action learning classification, providing a notable accuracy enhancement respect to other state-of-the-art solutions.

A case-based reasoning model to forecast the cost index of overhead transmission lines is provided in (Q. Xu et al., 2017). More freshly, the study (Cao & Ashuri, 2020) introduces a new DL-based algorithm (LSTM NN) for highway construction cost index prediction, which provides precise forecasts both in short, medium and long term; the model is trained with highway construction cost indexes from Texas Department of Transport.

In addition, the works (Fasanghari et al., 2015; Wauters & Vanhoucke, 2014) also present successful cost prediction in EVM, applying fuzzy NN and SVM respectively. What is more, Mortaji et al. (2013) use L-R fuzzy numbers to formulate EVM in vagueness environments for better planning, which provide efficient cost forecasting.

Moreover, the research (Oliveira et al., 2021b) develops a precise system that adopts DL with convolutional NN computer vision for the automatic remote monitoring of power substation construction management. Besides, Cheng et al.(2021) present 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 forecasting model. In addition, Umer et al.(2018) suggest an emotion-based automatic ML approach to predict the priority of a bug report.

Besides, several studies use AI techniques for the Project Monitoring and Controlling phase:

Al-subhi et al.(2021) apply 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 that contain diagnosis-decision-prediction attributes related to the PM knowledge areas of scheduling, cost, resource, quality and procurement, from the Research Database Repository for PM provided by the University of Informatics Sciences of Cuba. Performance results indicate that the novel proposal outperforms fuzzy cognitive maps and neutrosophic cognitive maps techniques, and experts expressed their satisfaction with the outcome obtained by the new suggestion.

The article (Vickranth et al., 2019) introduces 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 analysing worksite data with computer vision to predict the best continuity of construction activities in each scenario (e.g., doxel ai; which uses robots and drones with sensors to scan worksites, and DL for production assessment and guarantee safety).

Teizer (2015) presents an overview of computer vision-based sensing technology available for temporary resource tracking at infrastructure construction sites to plan and manage resources. It is concluded that robust and fast algorithms for long-term asset detection and tracking are a challenge to be addressed in future research. Further, Yang et al.(2015) review computer vision-based construction performance monitoring methods, which includes the visual monitoring of infrastructure/building, equipment and workers. Studies (Teizer, 2015; Yang et al., 2015) show the use of ML for the presented computer vision-based approaches.

The paper (García et al., 2017) analyses the trends of computational intelligence techniques such as ML to be applied to project control.

Amer et al. (2021) to eliminate manually aligning master schedules and lookahead plans, an approach for measurement of activities is presented that automatically maps master schedule activities to planning tasks. Their NLP-based method uses a state-of-the-art transformer, namely GPT-2, to automatically measure and map activities and tasks to one another.

Asnafi et al. (2021) propose the use of 5G technology, combined with BD, AI, state perception and video recognition technology, to establish the intelligent construction site visualization platform, that integrates with 3D model to realize 3D visualization display of information.

Table 7 provides a summary on the AI techniques for the measurement PD.

Table 7- AI-enabled Measurement PD

Purpose	AI technique	Reference
Earned Value Management (EVM) measurements	**SVM** **k-nearest neighbour** **RF** **Fuzzy approaches**	Fasanghari et al.(2015); Hajiali et al.,(2020) Wauters & Vanhoucke (2014), (2016), (2017) Fasanghari et al. (2015) Hajiali et al. (2020)
Delay measurements	**GA** **RF**	Yaseen et al.(2020) Boejko et al.(2012)
Activity measurement	**ML**	Akhavian & Behzadan, (2016) Yang et al.(2016)
Cost Performance Index	**NN** **Fuzzy approaches** **SVM**	Q. Xu et al. (2017) Cao & Ashuri (2020) Fasanghari et al.,(2015) Wauters & Vanhoucke,(2014) Mortaji et al. (2013)
Monitor activities	**DL** **ML** **Fuzzy approaches** **NLP**	Oliveira et al.(2021b) Cheng et al.(2021) Umer et al.(2018) Al-subhi et al.(2021) Vickranth et al.(2019) Teizer (2015) Yang et al.(2015) García et al. (2017) Amer et al. (2021) Asnafi et al. (2021)

4.2.8. Uncertainty PD

Choetkiertikul et al.(2016) provide a 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 modelling of the probability distribution of project task duration by means of fuzzy expert estimates and fuzzy numbers is suggested in (Samokhvalov, 2020), which achieves more accurate estimations than existing methods under information uncertainty.

Okudan et al.(2021) have designed and developed a well-performing project risk management tool that provides risk identification, analysis, response and monitoring by means of a ML approach via cased based reasoning. Although it employs risk-related knowledge from past construction projects, it may be applicable in others sectors with minor changes.

Furthermore, the literature review paper (Afzal et al., 2019) reveals 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.,(2018) provide a ML-based approach for developing leading indicators that classify sites in terms of their safety risk in construction projects. Five ML algorithms have been used for training the sets (decision trees, RF, Logistics Regression, k-nearest neighbour, SVM). Results show that RF gives the best prediction performance. In addition, an ACO model for planning safe construction site layout that considers different safety objective functions is introduced in (Ning et al., 2018).

Besides, the article (Qi et al., 2018) presents a stability prediction of construction projects based on ML algorithms. Case study results show that input missing data imputation and supervised learning outperforms predictive ML. Further, a framework based on fuzzy logic for digitalized PM is presented in (F. Xu & Lin, 2016); it is applied for risk management in a railway project in Africa.

Furthermore, Chou et al. (2013) introduce a fuzzy GA-based SVM model that gives accurate prediction of PPP dispute resolution outcome in construction. Moreover, Chou et al.(2014) propose an optimized hybrid AI method that integrates a fast messy GA with a SVM to forecast dispute propensity among stakeholders in PPP construction projects; GA-SVM provides better prediction accuracy than other baseline models. Further, Chaphalkar et al.(2015) assert 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.(2015) provide 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 project's riskiness via the experiences of project managers. Further, the article (Ali et al., 2017) employs fuzzy decision making for project selection under uncertainty.

Di Giuda et al. (2020) deal with the application of AI-based NLP in PM, with 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; predict risks in the bidding process of a project, by analysing the uncertainty in the bidding document and extracting from it the influencing factors for bidding/tender risk forecasting; define project requirements in the preliminary phase of the design and construction process, enabling more efficient integration of stakeholder inputs into the design, which can support automated compliance checking in BIM; automatically extract poisonous clauses from construction contracts; AI-based automatic monitoring of project progress, which uses data translated from text using NLP.

In addition, the explorative study (Greiman, 2020) presents some AI applications to manage megaprojects, most of them related with the management of workers safety and health. Predicting the presence of a disease, a risk condition, or the need for repairing heavy equipment are benefits of ML applicable to megaprojects. Apart from that, employing NLP would help a project-based firm extracting information regarding the perception of risk from hundreds of contracts.

Choi et al. (2021) attempt to predict the risk of contractor and support decision-making at each project stage using ML technology based on data generated in the bidding, engineering, construction, and operation and maintenance stages of EPC projects. As a result of this study, the Engineering Machine-learning Automation

Platform (EMAP), a cloud-based integrated analysis tool applied with BD and AI/ML technology, was developed.

Moreover, Relich and Nielsen (2021) point out an approach to develop a method for estimating the cost related to production and warranty at the early stage of an new product design project. Additionally, this approach verifies the possibility of changes at the early stage (e.g. in the number of prototype tests), for which the production and warranty cost could be reduced. A multilayer feedforward NN is trained according to a gradient descent algorithm with momentum and adaptive learning rate backpropagation. The results of the ANN and LR model are compared with the average of output variables to illustrate to what extent these models outperform the arithmetic average.

Besides, Oliveira et al. (2021a) describe the application of tools such as self-organizing maps and Bayesian networks, which may provide a greater assertiveness in the allocation of human and financial resources, via prior analysis of different scenarios, helping both in the prioritization and monitoring of activities associated with projects. Their research results show the potential reduction of uncertainties in development time, better fit of the work force to the type of project, and the reduction of reworks, positively impacting on the final costs, especially those projects with greater complexity involved.

Table 8 provides a summary on the AI techniques for the uncertainty PD.

Table 8- AI-enabled Uncertaity PD

Purpose	AI technique	Reference
Risk Identification	**ML** **NLP**	Choetkiertikul et al.(2016) Di Giuda et al. (2020) Oliveira et al. (2021a)
Probability distribution	**Fuzzy approaches** **NN**	Samokhvalov, 2020 Relich and Nielsen (2021)
Risk Management tool	**ML**	Okudan et al.(2021) F. Xu & Lin (2016) Choi et al. (2021)
Risk assessment	**Fuzzy approaches** **NN**	Afzal et al. (2019) Costantino et al.(2015) Ali et al. (2017)
Risk Indicators	**ML**	Poh et al.,(2018)
Risk mitigation	**ACO**	Ning et al., 2018
Stability prediction	**ML**	Qi et al., 2018

Dispute Risk management	**GA** **SVM** **NN**	Chou, et al. (2013), (2014) Chaphalkar et al.(2015)
Safety Risks	**ML** **NLP**	Greiman, 2020

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 PDs in general, AI reviews and its adoption in PM, application in a sector, etc.); these researches have been found mainly during the last two years.

Fridgeirsson et al.(2021) present a 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 ones by AI, especially in the planning phase for cost, risk and schedule estimation; its expected future effect on monitoring and controlling costs, schedules and risks appears also relevant. On the contrary, results indicate 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 (Hofmann et al. 2020) provides a matrix method to develop purposeful AI use cases in PM domain, where PM knowledge areas are in columns and AI functions (i. e., predicting, decision-making) in rows; in this way, a specific problem related to a PM knowledge area, that requires human ability to be solved, would be assigned to an AI function for being solved.

Moreover, the article (Ong & Uddin, 2020) gives 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 ML-based PM is commonly applied to: schedule and cost prediction, assist in project tracking, determine project attributes (by help of NLP), risk and resource management, and chatbots. Those current applications remain preliminary in the increasingly complex PM, with promising improvement in the future BD era. Furthermore, the essay (Niederman, 2021) 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 (even for gamification).

Furthermore, Alshaikhi and Khayyat (2021) investigate the impact of AI on the future of PM. They state that AI still requires skilled project managers to add value and investment. In the near future, both manpower and AI skills are required so that a positive outcome can be achieved. Thus, project managers need to build and develop the skills, which would focus on the areas where AI could not achieve it.

In another study, Auth et al. (2021) present a framework that defines the fundamental concepts for applying AI to PM comprising both the requirements of AI for the application domain PM as well as the requirements of PM for the solution domain AI. the results of an interview study with AI and PM experts were included, in which requirements and design factors were collected from both the PM and AI perspectives.

Besides, Ruiz et al. (2021) review a large number of AI learning techniques aimed at PM (e.g. ANN, FL, etc.). The analysis is largely focused on hybrid systems, which present computational models of blended learning techniques. The study provide a brief description of the main studies that are being carried out in the field of AI in relation to PM subjects such as tenders, project health, human resources, information technology, engineering and design, operations, supply chain, logistics and construction.

In addition Holzmann et al. (2022) address the impact of AI on PM based on a Delphi study with a panel of 52 PM experts who reflected on future potential AI applications for the PM Knowledge Areas. Their study provides a visionary perspective. The results of the study categorize relevant items in each of the PM Knowledge Areas, thus providing a useful and organized basis for future research on AI in each one of these areas. In addition, the most important functions to be supported by AI were identified in this study and can be used as outlines for further studies that will benefit the PM profession. The top-ranked functions are: create a project schedule, analyse 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.

Further, Zhu et al. (2022) point 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. Furthermore, in most cases, organizations with different sizes and years of experience make no difference in respondents' perceived impact of applications.

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

- Darko et al. (2020) present a scientometric study about the state-of-the-art of research on AI in the Architecture, Engineering and Construction (AEC) industry. This work corroborates 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 is commented that cost, productivity, safety, and risk management have been the mainstream issues in AI-assisted AEC research, which do not appear linked to BIM in the presented research network.
- By a literature search, (Akinosho et al., 2020) identifies 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 (2020) gives examples of applications of fuzzy hybrid techniques for construction PM: fuzzy ML combined with GA to predict labour 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 modelling to predict crew performance based on crew motivation levels.

- Makaula et al. (2021) develop a framework for AI in construction management. A theoretical framework based on the research findings is developed which illustrates the application of AI technologies across the project lifecycle and the results of each application. AI can be used in planning, design, simulation of construction projects, it can also be used in advanced project execution phases of construction as well as in sourcing of materials and modularisation of high-end and specialised construction material and modules.
- Wu et al. (2022) present a comprehensive review of bottom-level techniques and mainstream applications of NLP in the construction PM. the paper provides a state-of-the-art review appraising studies and applications of NLP in construction sector. In summary, the core functions of NLP, i.e., information extraction and document organisation have been largely improved with various techniques. NLP can also assist many downstream applications and enhance decision-making and management effectiveness.

Moreover, the editorial (Schuhmacher et al., 2021) provides an AI-enabled PM vision in the pharmaceutical research and development (R&D) context: 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 early mature phase of employing AI, it is expected to use ML in order to enhance its R&D decision making process before 2026. Further, (Endo & Kohda, 2020) deals 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.

Table 9 summarizes the main results from generic studies with their purposes related to AI application in PM.

Table 9- Generic studies on AI application in PM

Purpose	Main Result	Reference
Explore the expected effect of AI on PM knowledge areas	project cost, schedule and risk management are likely to be the most impacted ones by AI	Fridgeirsson et al.(2021)
Develop purposeful AI use cases in PM	Specific problem related to a PM knowledge area, that requires human ability to be solved, would be assigned to an AI function	Hofmann et al.(2020)
Insights about the existing application of AI in PM	ML-based PM is applied to schedule and cost prediction NLP determine project attributes	Ong & Uddin (2020)
Potential of AI, together with data analytics, in PM	AI-assisted PM will likely reduce repetitive PM tasks	Niederman (2021)
Impact of AI on the future of PM	AI still requires skilled project managers to add value and investment	Alshaikhi and Khayyat (2021)
Fundamental concepts for applying AI to PM	Requirements of AI application in PM and the requirements of PM for the AI factors were collected from both the PM and AI perspectives.	Auth et al. (2021)
AI hybrid techniques aimed at PM	Identification of techniques for tenders, project health, human resources, information technology, engineering and design, operations, supply chain, logistics and construction	Ruiz et al. (2021)
Impact of AI on PM	Most impacted PM tasks are create a project schedule, analyse 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	Holzmann et al. (2022)
Applications of smart technologies in PM	Progress tracking, real-time monitoring, and schedule estimation	Zhu et al. (2022)
AI-assisted PM in the construction sector		
AI in the Architecture, Engineering and Construction	Most often-used AI techniques in PM include GA, NNs, ML and fuzzy logic and sets, becoming a trend	Darko et al. (2020)
Application of DL for construction PM	construction cost prediction, workforce activity assessment, construction site safety, and structural health	Akinosho et al., 2020

	monitoring and prediction	
Applications of fuzzy hybrid techniques for construction PM	fuzzy M-GA to predict labour productivity, fuzzy ML with fuzzy multicriteria decision-making, fuzzy ML with fuzzy system dynamics to perform risk analysis, and fuzzy agent-based modelling to predict crew performance .	Fayek (2020)
Framework for AI in construction management	Identification of application of AI technologies across the project lifecycle in construction	Makaula et al. (2021)
Applications of NLP in Construction PM	core functions of NLP, i.e., information extraction and document organisation have been largely improved with various techniques	Wu et al. (2022)
AI-assisted PM in the pharmaceutical sector		
AI-enabled PM vision in the pharmaceutical research and development (R&D) projects	the pharmaceutical sector is in early mature phase of employing AI, it is expected to use ML in order to enhance its R&D decision making process before 2026	Schuhmacher et al., 2021
AI-assisted PM in the IT sector		
Use of AI (referring to ML and DL) to support the PM process in the digital transformation	almost all project managers have a positive attitude towards AI adoption in their current or near future projects	Endo & Kohda (2020)

5. Conclusion

Bibliometric results show a notable increasing number of high-impact publications related to AI-PM topic during the last decade. According to the findings, construction is the most impacted sector by AI, which could be due to the complexity of nature of construction megaprojects.

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 works have been found about AI-enabled project time forecasting and effort prediction. Further, several investigations exist about AI-based uncertainty PD (which includes safety uncertainties 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.

Besides, 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, fuzzy NN). Moreover, DL has become a trend in the last years, which gives solution 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.

AI technology has the capability to be used in PM for increasing the performance of the project and also bringing success and solutions for emerging management subjects in digital transformation towards industry 5.0.

As it is shown in the figure 8, AI techniques have been developed in construction, IT and other industry sectors to serve various PDs:

Stakeholders management would benefit from ML, NLP and NN for forecast litigation outcome, stakeholder classification and product owner engagement. AI-assisted communication in project using ML have the potential of increasing team performance.

For the purpose of planning, duration prediction, effort estimation, scheduling, assignment of human resources to project tasks, resource levelling, predicting project cost and effort estimation in agile projects, several AI techniques such as ML, fuzzy logic, NNs, GA, expert system, ACO, SVM-GA and DL have shown potential usefulness.

Contractor prequalification, communication with stakeholders, managing distributed information systems, execution scenarios and purchasing systems may use the fuzzy expert system, SVM, NLP, DL and NN to increase the performances in project works.

Compliance/conformance checking automation, project quality management, applying sustainable success index in project with the help of DL, NN and fuzzy algorithms bring the opportunity of efficient delivery of projects.

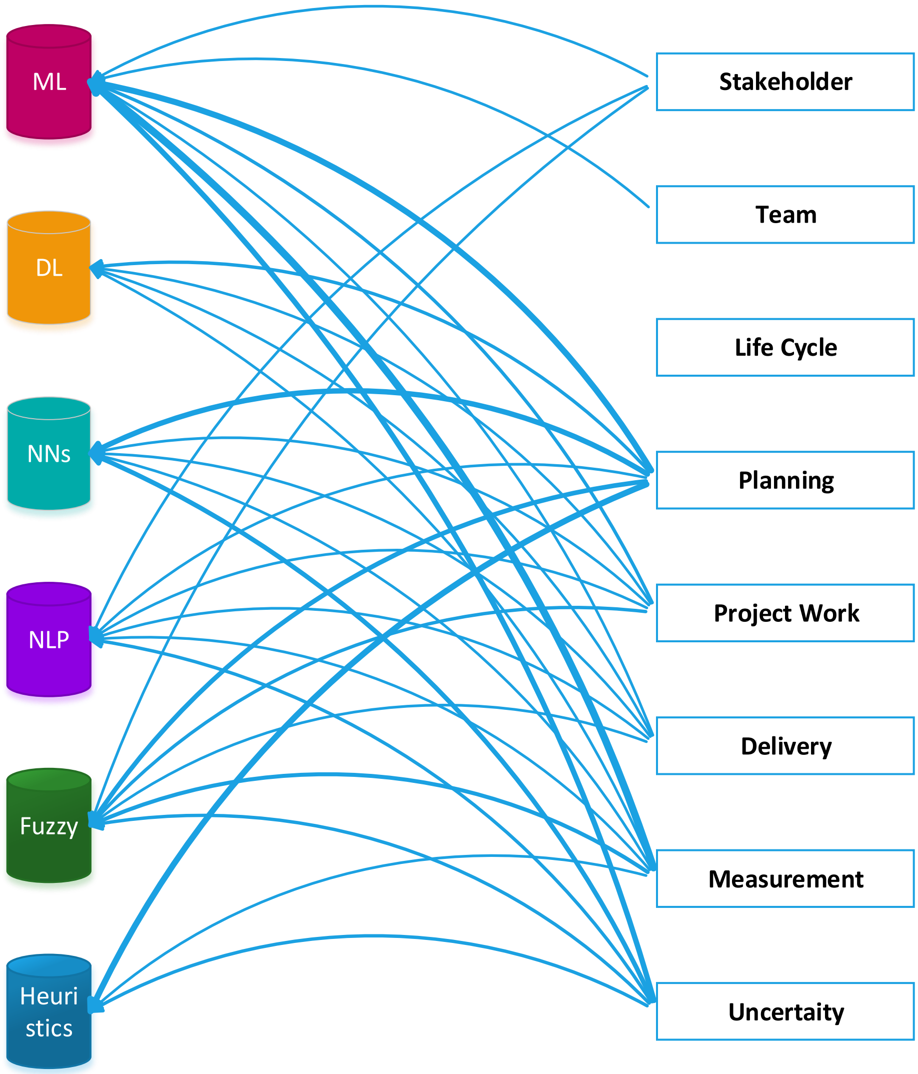

Figure 8- Identified AI techniques for PMPDs

Project duration forecasting in EVM, predicting delay levels in construction, recognizing the activity of workers, remote monitoring, project monitoring utilizing AI techniques (e.g. ML, SVM, GA, fuzzy and NN) has shown proficient measurement in projects.

AI enabled uncertainty features address the forecast the risk of a task, modelling of the probability distribution, risk assessment in construction projects, stability prediction, forecast dispute propensity, classifying the level of project's riskiness in the studies literature. ML, fuzzy, ANN, ACO and NLP are AI techniques that would be used for uncertainty functions.

While recent research attempt to demonstrate the present state of AI in PM and its future prospects, findings suggest that AI's application in real-world PM still is not in the mature state. The gaps in the literature concerning AI-based PM are summarized below:

- Lack of sustainability-aware AI-enabled PM.
- Lack of evidence of AI adoption for project managers.
- Lack of study on AI application in project development and lifecycle PD.
- Lack of framework compatible with PMTQ for AI-enabled PM.

The current study was limited to scientific papers published and advances in the AI-PM techniques which are not published are not covered.

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