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Advances of Artificial Intelligence in Organizational Project Management: A Systematic Literature Review

Avances de la Inteligencia Artificial en la Gestión Organizacional de Proyectos: Una Revisión Sistemática de Literatura

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ABSTRACT

Organizational project management (OPM) encompasses three key domains: program management, portfolio management, and project management (PM), in addition to organizational enablers. Research indicates increasing application of artificial intelligence (AI) technologies within OPM. However, an analysis of published literature reviews on the topic reveals significant advancements primarily within the PM domain, with limited progress observed in program management, portfolio management, and organizational enablers. Therefore, this study seeks to identify progress in AI applications across all three domains and organizational enablers within OPM to establish emerging trends and highlight future research opportunities. A systematic literature review was conducted utilizing the SCOPUS and Web of Science databases. After applying a series of filters, 87 publications were selected for analysis. The study identifies AI applications in four types of tasks related to OPM: routine, decision-making, judgment, and problem-solving. Results indicate that while application of AI technologies remains primarily focused on PM, there are new advancements in program and portfolio management. However, they occur mainly in operational processes; strategic aspects remain largely underdeveloped. Regarding organizational enablers, similar to the previously published review papers, no AI applications are reported. This study identifies organizational challenges and research opportunities in four main areas: data collection, development of algorithms tailored to project requirements, human resource management, and ethical practices.

Keywords: Organizational Project Management, Artificial Intelligence, Project Management, Portfolio Management, Program Management.

R E S U M E N

La Dirección Organizacional de Proyectos (OPM) comprende tres dominios fundamentales: la gestión de proyectos (PM), la gestión de programas y la gestión de portafolios, además de los habilitadores organizacionales que facilitan su implementación. La literatura científica muestra un creciente interés en la aplicación de tecnologías de inteligencia artificial (IA) dentro de este campo. No obstante, al revisar los estudios existentes, se evidencia que los avances más notorios se han dado en el ámbito de la gestión de proyectos, mientras que la gestión de programas, la gestión de portafolios y los habilitadores organizacionales han recibido menos atención investigativa. Este estudio tiene como objetivo identificar el progreso en las aplicaciones de IA en los tres dominios de la OPM y en sus habilitadores, con el fin de reconocer tendencias emergentes y proponer nuevas líneas de investigación. Para ello, se realizó una revisión sistemática de la literatura en las bases de datos SCOPUS y Web of Science. Tras aplicar criterios de selección, se analizaron 87 publicaciones. El estudio clasifica las aplicaciones de IA en cuatro tipos de tareas: rutinarias, toma de decisiones, juicio y resolución de problemas. Los resultados muestran que, aunque el enfoque sigue centrado en PM, comienzan a aparecer desarrollos en programas y portafolios, principalmente en procesos operativos. Los aspectos estratégicos y los habilitadores organizacionales siguen poco explorados. Se identifican oportunidades de investigación en áreas clave como recolección de datos, desarrollo de algoritmos específicos, gestión de recursos humanos y consideraciones éticas.

Palabras clave: Gestión Organizacional de Proyectos, Inteligencia Artificial, Gestión de Proyectos, Gestión de Portafolios, Gestión de Programas.

1. INTRODUCTION

Organizational project management (OPM) integrates three key management areas: portfolios, programs, and projects, along with organizational enablers (PMI, 2017a). Among these three domains, project management (PM) —the most widely recognized— is defined as a temporary endeavor that employs knowledge, skills, tools, and techniques to meet project requirements (PMI, 2017a). To implement OPM, various processes and activities have been designed (PMI, 2017a). However, despite advancements, a significant number of projects fail to meet their objectives within the established time and budget, with failure rates ranging from 20% to 60% (Project Management Report, 2023). For instance, Portman (2021) reports a success rate of 31% in the software sector.

At the organizational level, these failures are attributed to various factors. These include a lack of alignment between the project portfolio and organizational strategy, and methodological deficiencies arising from poorly structured processes (Pakdaman *et al.*, 2021). Additionally, project complexity is exacerbated by inadequate collection and analysis of data, coupled with non-adaptation of management practices to project-specific requirements (Pakdaman *et al.*, 2021; Szalay *et al.*, 2017).

The advent of new technologies (artificial intelligence, data analytics, robotics), has led to performance enhancement across multiple domains of business management. According to the Global Artificial Intelligence Innovators survey, 81% of companies are being impacted by AI, and 85% of CEOs believe that this technology will transform the way business is conducted in the future (Skinner, 2021; Taboada *et al.*, 2023). AI is already being applied in numerous sectors, including computing, mathematics, engineering, medicine, and research. This technology is expected to drive a shift toward standards, processes, and tools that are more aligned with business strategy, rather than relying on traditional methods focused on operational outcomes (Holzmann *et al.*, 2017).

Organizations are integrating AI to automate both internal and external operations (Enholm *et al.*, 2022).

From an internal perspective, AI implementation aims to optimize organizational performance, enhance decision-making, and foster innovation (Przegalinska *et al.*, 2025). Externally, AI promotes companies' ability to identify new market niches and adapt to dynamic economic conditions (Uriarte *et al.*, 2025). However, its adoption involves multiple challenges, including appropriate technological infrastructure, employee competencies, management and leadership practices, organizational culture and structure (Tomaževič *et al.*, 2024), profitability (Prasad Agrawal, 2024), and scalability based on company size (Al-Kfairy, 2025). Additionally, there exist concerns regarding ethical and regulatory implications (Alawamleh *et al.*, 2024; Rezaei *et al.*, 2024), as well as the lack of a comprehensive understanding of its implementation in the business environment (Enholm *et al.*, 2022).

Evidence suggests that successful projects are intimately linked to organizational management capability; in other words, the greater the capability, the higher the success rate (Karim *et al.*, 2022). In the PM domain, Tariq *et al.* (2024) demonstrated that a higher level of AI implementation produces better results in terms of efficiency, compliance, product quality, and reduced human errors. However, merely 23% of projects worldwide have incorporated AI technologies, and in Latin America, this is slightly higher, at 25% (Skinner, 2021).

Regarding the review studies on AI applications in OPM, 21 contributions were identified in the literature. Despite this significant number of studies, our analysis reveals that most advancements have been reported within the PM domain (Belharet *et al.*, 2020; Hashfi & Raharjo, 2023; Mishra *et al.*, 2023; Taboada *et al.*, 2023). Research indicates that in this domain, AI has been particularly effective in automating and managing schedules and budgets. Gramberg *et al.* (2024) emphasize an adaptive evaluation system with new performance indicators and specialized methods to assist companies adjust their product portfolios in response to the challenges posed by disruptive technologies such as AI. The published review studies highlight a significant presence of AI applications in financial and construction projects. In finance, AI has primarily been applied for customer segmentation and resource allocation; however, adoption remains sluggish because of transparency concerns. In construction, AI has significantly advanced in the contexts of cost management, scheduling, quality control, and scope management.

Other applications include project selection, risk assessment, and enhancement of the overall success rate (Hashfi & Raharjo, 2023). Müller *et al.* (2024) emphasize that AI has primarily impacted improvements in efficiency, accuracy, and support for operational decision-making in PM. Generally, the published literature review studies indicate a concentration of AI applications in short- and medium-term planning and execution processes, while revealing gaps in long-term perspectives, including strategic organizational planning. Moreover, no review studies were identified that reported relevant advancements of AI in program management, portfolio management, or in the organizational enablers of OPM, highlighting the need for further research in these areas.

Therefore, this study aimed to conduct a broader review of AI advancements across the three domains of OPM: portfolios, programs, and projects, as well as their organizational enablers. To achieve this, two research questions are posed: (1) *In which processes of the three OPM domains and their enablers have AI tools been implemented*? and (2) *What are the future research areas related to AI applications in OPM*? To answer these questions, a systematic literature review was conducted using the Scopus and Web of Science (WoS) databases, following the checklist proposed by Williams *et al.* (2021) and Ferreira de Araújo Lima *et al.* (2020). After applying a series of filters, 87 publications were included, supplemented by a narrative review in areas with limited information.

Our literature review indicates that while most advancements in AI applications remain concentrated in the PM domain, progress has also been observed in program and portfolio management. AI has had the greatest impact on cost, time, and human resource management, largely driven by the availability of databases that facilitate algorithm implementation. However, challenges persist, including insufficient data collection throughout the project lifecycle and the lack of algorithms capable of integrating multiple AI tools into hybrid systems. Organizational challenges and future research opportunities were identified in four key areas: databases, algorithms, human management, and ethical concerns.

2. CONCEPTUAL FRAMEWORK

2.1. Organizational Project Management (OPM)

OPM serves as a veritable bridge between an organization's vision and mission and the ongoing portfolio, program, and project initiatives. Based on coordination, alignment, and implementation, it aims to achieve the strategic objectives of the organization, striving for sustainable competitive advantage. As illustrated in Figure 1, OPM integrates a conceptual framework where its three domains (portfolio management, program management, and project management) converge with organizational enablers to attain strategic goals. Processes represent a systematic series of activities aimed at producing an outcome, acting on one or more inputs to create one or more outputs. Practices refer to specific types of activities that contribute to the execution of a process and may employ one or more techniques or tools.

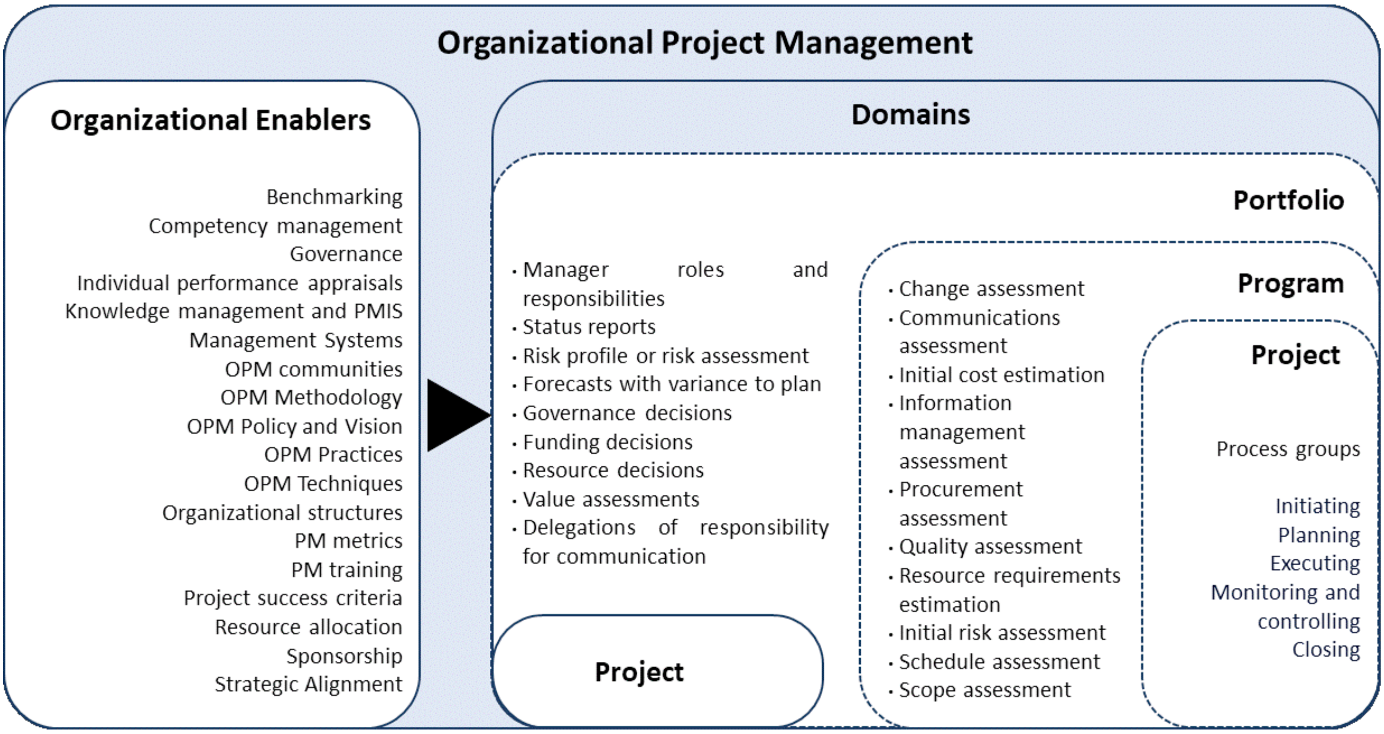

Figure 1

Domains and Organizational Enablers of OPM

Source: Author's own elaboration based on PMI (PMI, 2017b, 2017a, 2018, 2017c).

The portfolio encompasses a collection of programs, projects, and operations collectively managed to achieve strategic objectives. Portfolio management centralizes one or more portfolios to align activities with the organizational strategy, selecting and prioritizing the appropriate programs or projects while allocating the necessary resources (PMI, 2018). Programs consist of related projects and coordinated activities to achieve benefits that cannot be obtained by managing them individually. Program management harmonizes program components, controls their interdependencies, and manages transformational change to realize defined benefits (PMI, 2018). PM focuses on developing and executing plans to fulfill a specific scope, aligned with the objectives of the corresponding portfolio or program and the organizational strategy (PMI, 2018). This domain is organized into process groups (initiating, planning, executing, monitoring, controlling, and closing) and knowledge areas such as integration, scope, schedule, cost, quality, resources, communications, risks, procurement, and stakeholders (see Figure 2).

Mishra *et al.* (2023) proposed a typology to classify PM tasks based on their complexity: repetitive tasks, decision tasks, judgment tasks, problem tasks, and diffuse tasks. Repetitive tasks are straightforward and follow predefined steps, such as data entry or managing schedules and budgets. Decision tasks involve choosing among various options, while judgment tasks require analyzing information to forecast future events, such as assessing a project's viability. Problem tasks comprise evaluating different approaches to achieve a goal, such as adjusting targets during development. Diffuse tasks are the most complex, encompassing multiple objectives and methods, such as cost or risk assessment models using machine learning (ML). Conversely, organizational enablers represent the structural, cultural, technological, or human resource practices that an organization employs to achieve its strategic objectives (PMI, 2018). These enablers comprise 18 categories, involving practices that support process management across the three domains.

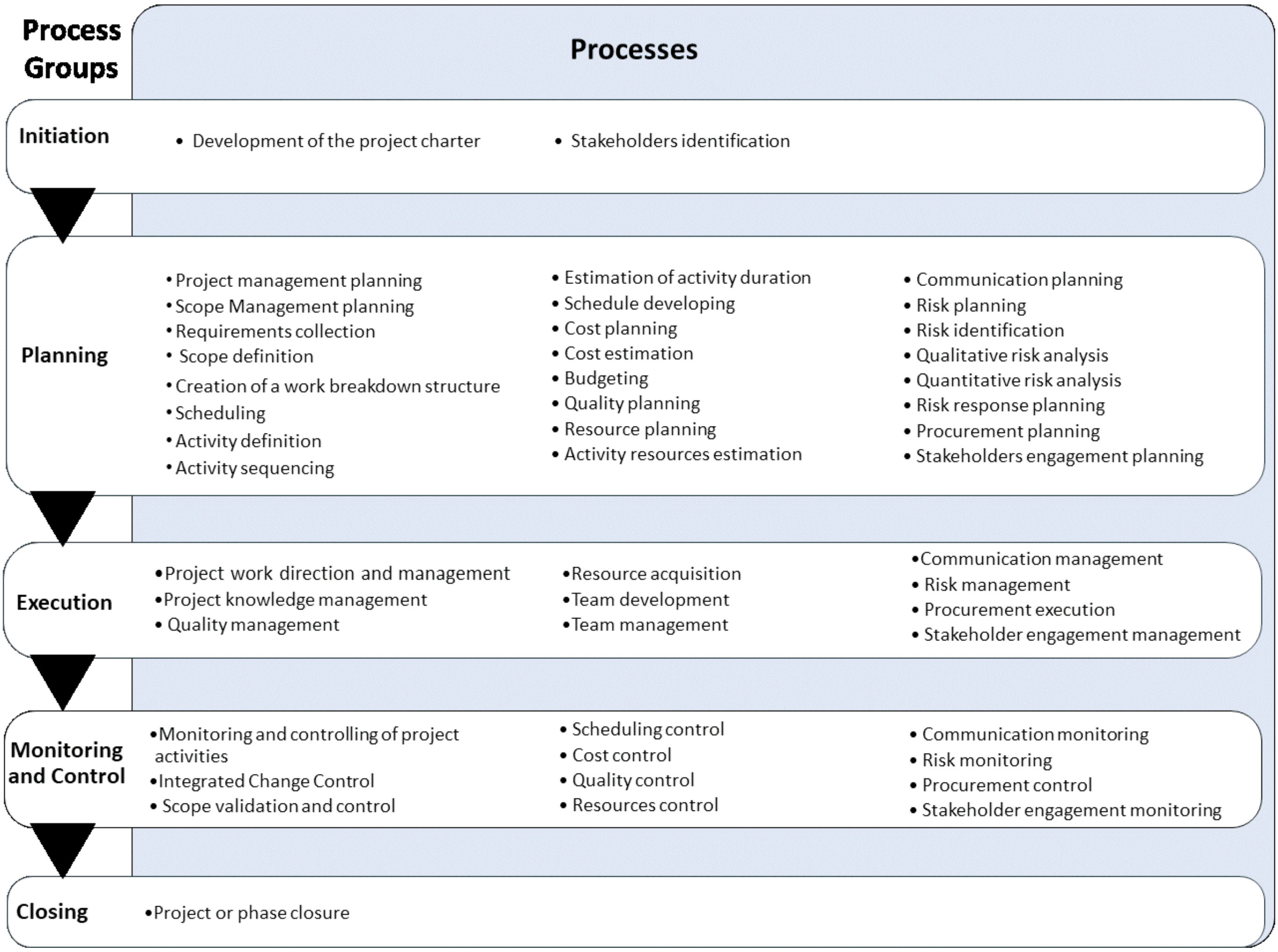

Figure 2
Processes and Process Groups in PM
Source: Author's own elaboration based on PMI (2017a).

2.2. Artificial Intelligence (AI)

AI replicates human knowledge to automate and expedite tasks traditionally performed using natural intelligence (AWS, 2024). AI systems comprise three primary software components: a database, an expert system, and a result-processing module (Radhakrishnan & Jaurez, 2021). The database serves as the foundational element, built from information gathered from similar projects and essential for any AI initiative. The expert system acts as the core engine, processing this data via integrated algorithms. Finally, the result-processing module either presents the outcomes to the user or archives them within the prediction system.

ML is a branch of AI that continuously improves models using data and algorithms, optimizing predictions (AWS, 2024). Based on mathematical and statistical processes, ML detects patterns in the data, which are then utilized to generate increasingly accurate predictions based on historical and new data. ML is categorized into two main types: supervised learning, where the model is trained with labeled data (with predefined inputs and outputs), and unsupervised learning, which seeks patterns in unlabeled data. Deep learning (DL) is a subcategory of ML that employs multi-layered neural networks, mimicking the functioning of the human brain to identify patterns and train models (AWS, 2024). DL architectures enable models to learn data representations at multiple levels of abstraction. Each processing layer transforms the input to enhance selectivity and accuracy in classification.

Big Data and data science are foundational pillars of AI, intimately inter-related and mutually reinforcing. Big Data encompasses the collection of voluminous information that necessitate rapid and sophisticated processing. The exponential growth of such data has driven the creation of novel methods to understand and leverage it, as traditional techniques are insufficient for effective management (Zabala-Vargas *et al.*, 2023). Conversely, data science is an interdisciplinary field that utilizes methods, algorithms, and systems to extract meaningful insights from both structured and unstructured data. AI leverages these processed insights to enhance its training (Zabala-Vargas *et al.*, 2023). As data collection continues to expand, AI algorithms —particularly those in ML and DL— become increasingly accurate, boosting efficiency, improving decision-making, and driving innovation.

3. LITERATURE REVIEWS OF AI APPLICATIONS IN OPM

Table 1 presents the literature reviews conducted over the past five years on AI applications in OPM. Of the 21 articles identified, 12 focus on AI applications within the PM domain and five within the portfolio domain. Notably, no review studies were identified reporting applications in the program management domain or in organizational enablers. Additionally, four studies explored application of AI technologies in construction projects. However, none of them classifies the applications within OPM domains or organizational enablers.

Table 1
Previous Literature Review of AI Applications in OPM

Author(s)	**OPM domains***			**Organizational enablers**	**Sector**	**Main contributions**
	Pr	**Po**	**PM**			
Prasetyo *et al.* (2025)			x	Not addressed	Industry	Identification of the requirements for the successful application of AI in PM
Ongesa *et al.* (2025)			x	Not addressed	Health	A PM approach using AI for public health preparedness and response projects in urban health crises
Harnessing AI in Entrepreneurial Project Management, (2024)			x	Not addressed	Not declared	Identification of the potential and challenges of AI in business PM
Senescall & Low (2024)		x		Not addressed	Financial	Contributions of ML to predicting future asset behavior and addressing non-convex optimization challenges
Kiani (2024)			x	Not addressed	Not declared	Analysis of AI in replacing human functions and its impact on digital transformation
Aamer *et al.* (2024)			x	Not addressed	Not declared	Emerging technologies' effects on project management are analyzed, identifying benefits in schedule control and cost planning
Nenni *et al.* (2024)		x		Not addressed	Not declared	The intersection of project risk management and AI is explored
Amato *et al.* (2024)		x		Not addressed	Financial	The automation of customer segmentation techniques, focusing on credit portfolio management, is studied
Sutiene *et al.* (2024)		x		Not addressed	Financial	AI contributions to portfolio management are reviewed.
Zabala-Vargas *et al.* (2023)				Not addressed	Construction	The utilization of Big Data, data science, and AI in construction projects is reviewed
Taboada *et al.* (2023)			x	Not addressed	Not declared	The impact of AI application on PM performance is studied
Hashfi & Raharj (2023)			x	Not addressed	Not declared	The relationship between AI and PMBOK process groups is analyzed, highlighting AI's effectiveness in improving risk assessment, cost prediction, and decision-making throughout all PM phases
Mishra *et al.* (2023)			x	Not addressed	Not declared	The integration of AI and ML into IT project management to enhance decision-making, risk management, and efficiency is discussed
Bento *et al.* (2022)			x	Not addressed	Not declared	AI tools are identified as enhancing various aspects of PM across different phases of the project life cycle
Hanjing *et al.* (2022)				Not addressed	Construction	The impact of smart technologies on construction PM is explored
Borges *et al.* (2021)			x	Not addressed	Not declared	The main strategic applications of AI in PM are identified
Huang *et al.* (2021)				Not addressed	Construction	A comprehensive review of technological changes, resulting processes, and organizational modifications in the context of Big Data in PM is conducted
Belharet *et al.* (2020)			x	Not addressed	Not declared	The study explores the evolution and transformation of PM as it adapts to AI advancements
Gil-Ruiz *et al.* (2020)			x	Not addressed	Not declared	The trend of combining different AI tools in PM is demonstrated
Yamakawa *et al.* (2019)		x		Not addressed	Financial	Tools to support decision-making challenges involving optimization, statistical techniques, simulations, and AI are identified
Sharma and Goyal (2019)				Not addressed	Construction	The applications of fuzzy logic in construction projects are studied

Pr: Program Management; Po: Portfolio Management; PM: Project Management.

Source: Author's own elaboration.

In the PM domain, literature reviews have focused on the impact of AI across various processes, primarily in the phases of project planning, execution, monitoring/control, and closure (Aamer *et al.*, 2024; Belharet *et al.*, 2020; Hashfi & Raharjo, 2023; Mishra *et al.*, 2023). Specifically, Belharet *et al.* (2020) examined the knowledge areas and industry types where AI has been implemented in PM, highlighting its utilization in cost estimation, resource allocation, and quality and productivity management (Hashfi & Raharjo, 2023). Other applications include stakeholder management, team coordination, lifecycle planning, and uncertainty management (Aamer *et al.*, 2024; Taboada *et al.*, 2023). A common consensus among these studies is that AI has significantly improved decision-making within PM operational processes. Borges *et al.* (2021) and Prasetyo *et al.* (2025) emphasize aligning AI technologies with strategic decision-making, product and service management, and client and employee engagement to create competitive advantages. However, Taboada *et al.* (2023) indicate the lack of research into comprehensive AI-based PM frameworks that address lifecycle considerations, sustainability, and technology adoption by project managers.

In portfolio management, AI applications have been more prevalent in the financial sector, particularly for customer segmentation based on credit history and for mitigating risks associated with credit lending (Amato *et al.*, 2024; Nenni *et al.*, 2024; Senescall & Low, 2024). AI has also been utilized for resource allocation in financial projects (Yamakawa *et al.*, 2019). However, the adoption of AI in this sector has been sluggish, largely because of the need for transparency and explainability, which has induced uncertainty around its implementation (Sutiene *et al.*, 2024). In the construction industry, AI has made significant advances, driven by the complexity of projects that demand synchronized and real-time information. Algorithms such as fuzzy set, fuzzy logic, and fuzzy neural networks have supported decision-making, improved planning, automated tasks, and increased efficiency throughout project phases (Huang *et al.*, 2021; Sharma & Goyal, 2019). Key AI applications in this industry pertain to cost management, scheduling, quality, and scope (Hanjing *et al.*, 2022; Zabala-Vargas *et al.*, 2023).

Despite progress in PM, literature reviews indicate a concentration of AI applications in short- and medium-term planning and execution processes. Long-term perspectives, including strategic organizational planning, have remained underexplored. Furthermore, there exists an explicit need for continued research into AI implementation across other domains of OPM and its organizational enablers.

4. METHODOLOGY

The review method adhered to the checklist proposed by Williams *et al.* (2021) and Ferreira de Araújo Lima *et al.* (2020), aligned with the stages outlined in Figure 3. During the planning stage, the need was identified based on the following research questions: (1) *In which processes across the three OPM domains and their enablers have AI tools been implemented*? and (2) *What are the future research areas regarding AI applications in OPM*? During the direction stage, we defined the search strategy, selection criteria, quality assessment criteria, data extraction strategy, and data synthesis approach. Additionally, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) checklist was utilized. It pertains to the information necessary to ensure the rigor of the review process (Briner & Denyer, 2012).

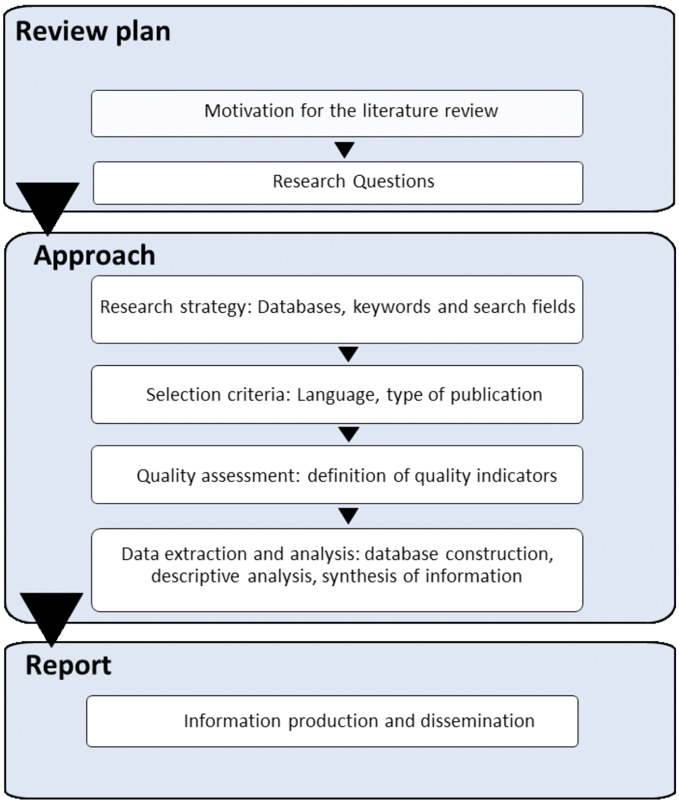

Figure 3
Systematic Literature Review Method
Source: Author's own elaboration based on Williams *et al.* (2021) and Ferreira de Araújo Lima *et al.* (2020).

The Scopus and WoS databases were chosen for the search because of their extensive breadth and coverage (Pranckutė, 2021). The formulated search equation, based on the intersection of the relevant topics, is presented in Figure 4. In both databases, only research articles and review articles published in English within the last 10 years (from 2014 to February 2025) were included.

Figure 5 illustrates the filtering process, while Table 2 outlines the inclusion and exclusion criteria applied in the review. As shown, out of the 838 documents identified in Scopus, 621 were excluded because they were book publications, theses, conference papers, out-of-date, or in another language. Consequently, only 217 documents were analyzed in the review phase. A similar process was followed for the WoS, starting with 217 publications, which, after filtering, resulted in 164 documents for the review phase. During this phase, an additional filter was applied based on a detailed abstract analysis, leading to a final selection of 163 articles from Scopus and 81 from the WoS, totaling 244 documents. Finally, after comparing both databases, 157 duplicate articles were identified, resulting in a final analysis of 87 unique articles.

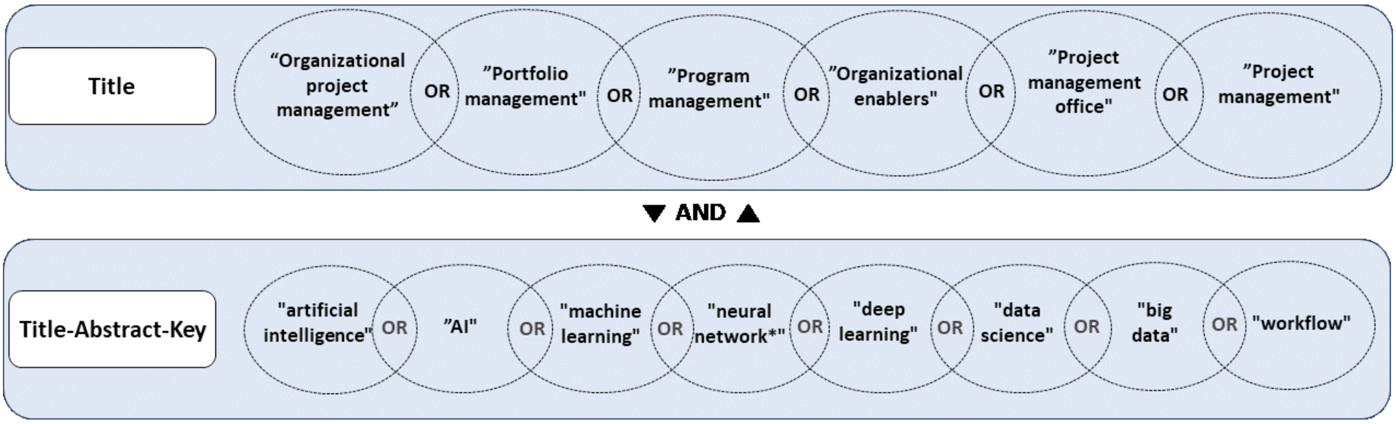

Figure 4
Search Equation for the Systematic Literature Review
Source: Author's own elaboration.

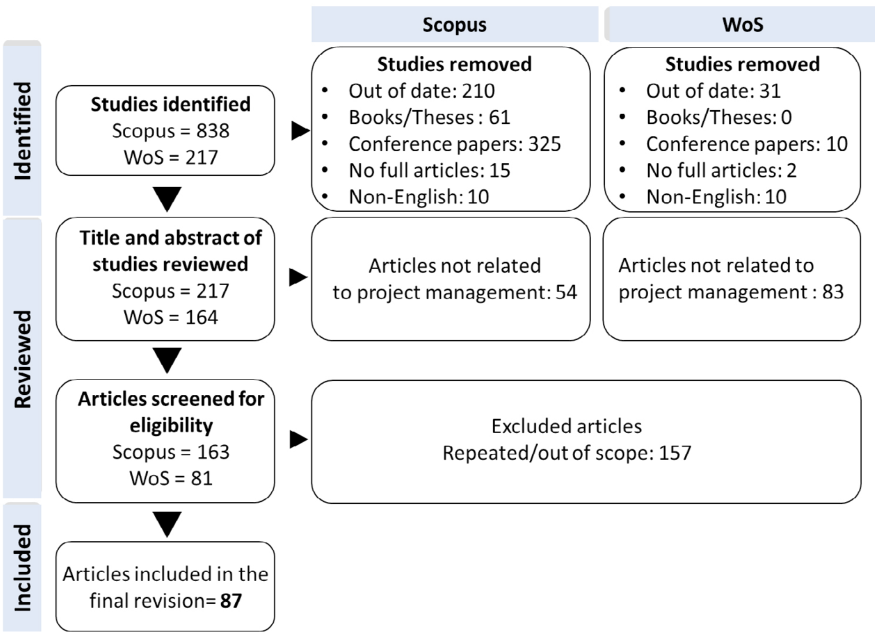

Figure 5
Document Search and Selection Process
Source: Author's own elaboration based on Briner and Denyer (2012).

Table 2
Inclusion and Exclusion Criteria Applied in the Literature Review

Inclusion Criteria	Exclusion Criteria
— Full-text availability — Published in English — Publication time frame: last 10 years (2014-February 2025) — Document type: articles and reviews — Articles related to the domains of OPM — Articles directly related to PM	— Abstract-only availability — Language other than English — Publication time frame: before 2014 — Document type: proceedings, book chapters, books, notes, short communications, among others — Articles not related to OPM or PM — Duplicate documents

Source: Author's own elaboration.

5. RESULTS: AI APPLICATIONS IN OPM PROCESSES

This section discusses the findings from the literature review aimed at addressing the first research question. Table 3 presents the processes categorized according to the task typology proposed by Mishra *et al.* (2023), along with the OPM domains where AI applications were identified. A total of 13 processes were impacted by AI, with the majority occurring in the PM domain, followed by portfolio and program management. Notably, no AI applications were identified within the organizational enablers, aligning with the literature review studies referenced in Table 1, nor in processes related to diffuse tasks.

Table 3
AI Applications in OPM Processes

		OPM domains*			
Task typology	**Processes**	**Pr**	**Po**	**PM**	**Author(s)**
Repetitive	Data entry		x		Pantović *et al.* (2024)
	Human resource management	x	x		Elkholosy *et al.* (2022)
		x			Yang *et al.* (2021)
				x	Alzeyani & Szabó (2024); Babu *et al.* (2024); Imeri and Imeri (2024)
	Time management / scheduling		x		Zhang *et al.* (2024)
				x	Alzeyani & Szabó (2024); Auth *et al.* (2021); Cinkusz *et al.* (2024); Ekanayake *et al.* (2024); Gil-Ruiz *et al.* (2020); Harish Kumar and Srinivas (2024); Hashfi and Raharjo, (2023); Jaafar *et al.* (2022); Liu and Hao (2021); Santos *et al.* (2023); Wang *et al.* (2012)
	Communication management		x		Müller *et al.* (2024);
				x	Cinkusz *et al.* (2024); Chen *et al.* (2021) Iordache & Marian (2024)
	Stakeholders		x		Müller *et al.* (2024)
				x	Chen *et al.* (2021)
	Document management		x		Müller *et al.* (2024)
				x	Chen *et al.* (2021)
	Cost management/ budgeting			x	Almahameed & Bisharah (2023); Alzeyani & Szabó (2024); Chen (2022); Farouq (2021); Harish Kumar & Srinivas (2024); Hashfi & Raharjo, (2023); Indhujaa & Jaisankar (2024); Jaafar *et al.* (2022); Ong & Uddin (2020); Santos *et al.* (2023); Wang *et al.* (2012); Wig & Martinez (2019)
Decision	Selection			x	Pantović *et al.* (2024); Sommer (2024); Sakka *et al.* (2023)
			x		Bai *et al.* (2022); Costantino *et al.* (2015); Ghapanchi *et al.* (2012); Rabbani *et al.* (2010); Wang *et al.* (2012)
		x			Singh (2015)
	Quality management, WBS/tasks			x	Aamer *et al.* (2024); Auth *et al.* (2021); Cinkusz *et al.* (2024); Hanjing *et al.* (2022); Holzmann *et al.* (2022); Si *et al.* (2023)
Judgment	Risk management		x		Bilgin *et al.* (2022) Zaidouni *et al.* (2024)
				x	Choi *et al.* (2021); Krichevsky *et al.* (2019); Mohamad *et al.* (2021); Mohite *et al.* (2023); Wei & Ding (2022); Wig & Martinez (2019); Taye and Feleke (2022)
	Planning control			x	Gil-Ruiz *et al.* (2020); Grabis *et al.* (2019); Hashfi & Raharjo (2023); Jaafar *et al.* (2022); Mostofi *et al.* (2024); Santos *et al.* (2023); Wei & Ding (2022); Yang (2024)
			x		Liu (2019)
		x			Yang *et al.* (2021)
Problem	Scope management			x	Kraiem *et al.* (2023); Merzouk *et al.* (2023)
	Strategic alignment			x	Antony-Ranesh & Samuel (2022); Jang (2022)
Diffuse	Not found	—	—	—	

Pr: Program Management; Po: Portfolio Management; PM: Project Management.

Source: Author's own elaboration.

Figure 6 depicts the distribution of studies by domain, task typology, and processes. The data indicate that the PM domain encompasses the majority of AI applications (79%), followed by portfolio management (16%) and program management (5%). Most applications are concentrated in repetitive or routine tasks (49%), especially in cost/budget management and scheduling. Significant advancements are also noted in risk management (judgment tasks) and project selection (decision tasks). Conversely, decision-making, problem-solving, and diffuse tasks exhibit less progress in terms of AI applications.

Figure 7 illustrates the most widely used AI algorithms in OPM. The most frequently applied algorithms include neural networks, fuzzy logic, and random forests, whereas digital twins and genetic algorithms are used less often. All identified algorithms have been implemented in the PM domain. In portfolio management, neural networks and fuzzy logic stand out, while program management employs only four algorithms, including random forests. Figure 7 showcases the AI algorithms utilized according to task type. Most algorithms are predominantly utilized in repetitive tasks, with the exception of Bayesian networks and digital twins, which are mainly applied in judgment and decision-making tasks, respectively.

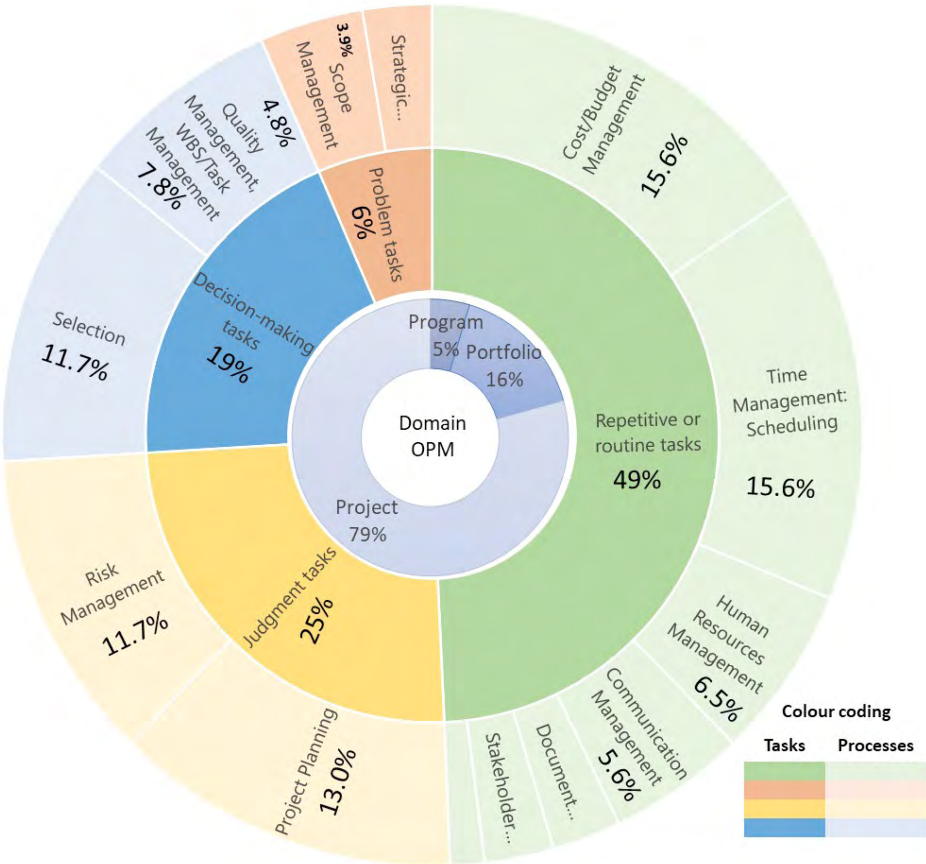

Figure 6
AI Applications in OPM Domains, Tasks, and Processes
Source: Author's own elaboration.

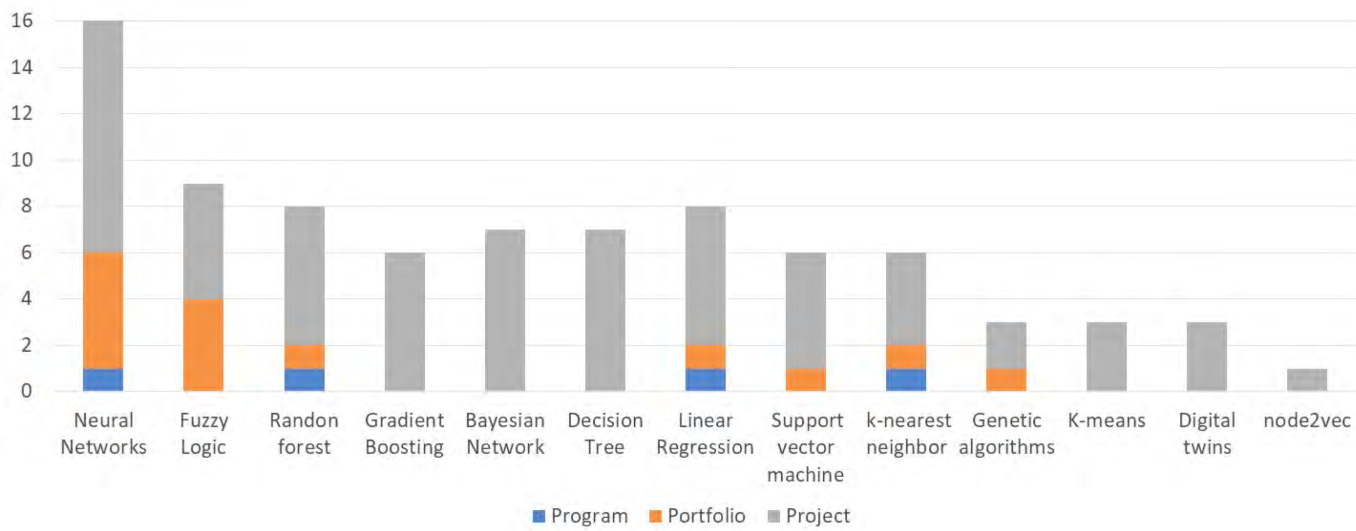

Figure 7
Most Utilized AI Algorithms in OPM Domains
Source: Author's own elaboration.

Figure 8 depicts the processes associated with repetitive tasks and the AI algorithms utilized. AI is pivotal in human resource management, cost management, and time management, with Bayesian networks being the most commonly applied algorithms across various processes.

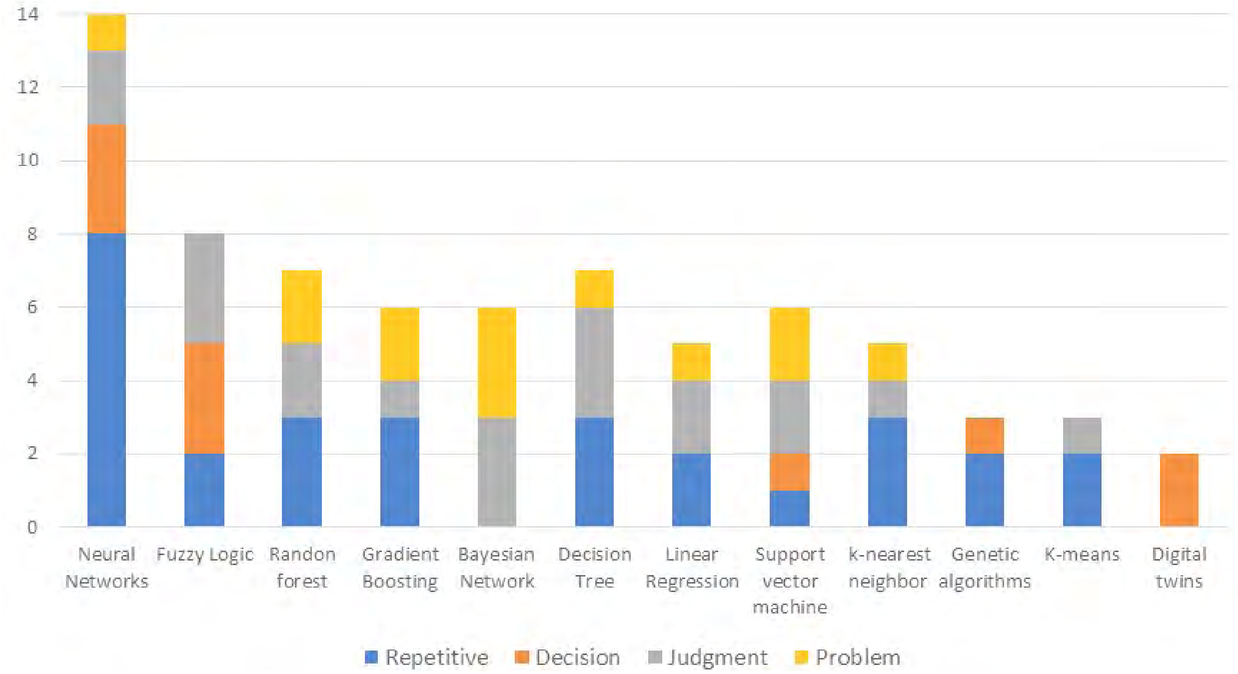

Figure 8
Most Utilized AI Algorithms by Task Type
Source: Author's own elaboration.

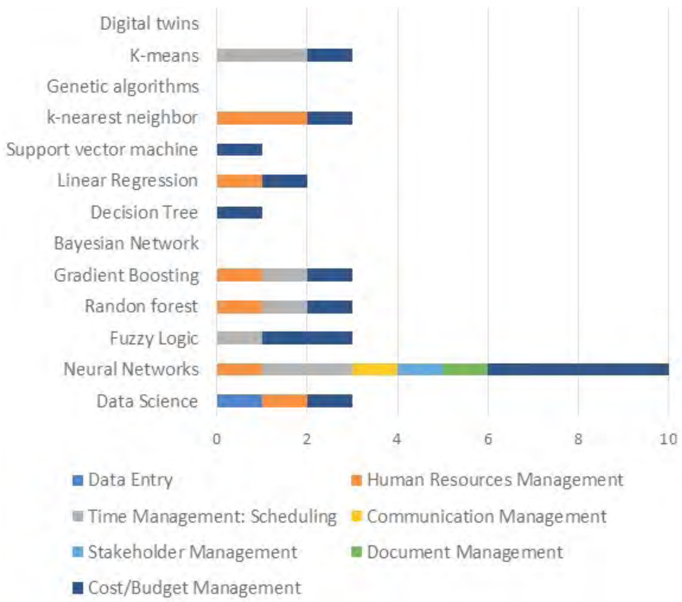

Figure 9
Most Utilized AI Algorithms by Process Type: Repetitive Tasks
Source: Author's own elaboration.

Neural network-based algorithms are the most commonly used for repetitive tasks (Figure 9). In decision-making tasks (Figure 10), digital twins are prominent in selection and quality management processes, while genetic algorithms are employed for selection and control in judgment tasks (Figure 11). Finally, Figure 12 shows that the most widely accepted algorithm for problem-solving tasks are Bayesian networks. Although not considered AI algorithms, data science is utilized for data entry and in human resource management, cost management, selection, and control. Overall, studies apply multiple algorithms to a dataset to identify which one produces the most favorable results.

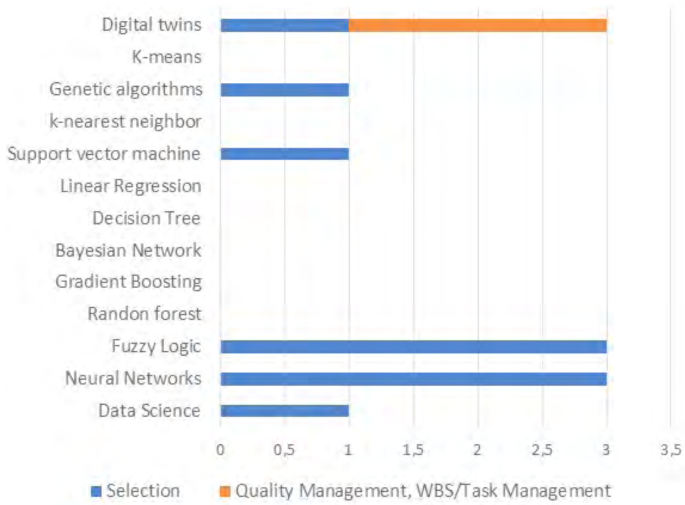

Figure 10
Most Utilized AI Algorithms by Process Type: Decision-making Tasks
Source: Author's own elaboration.

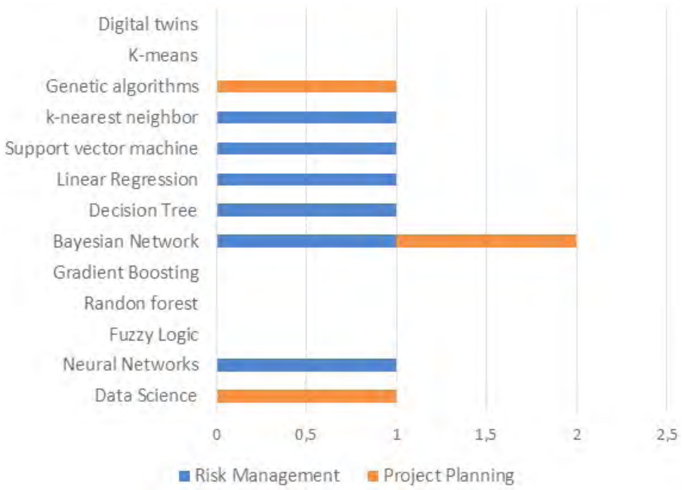

Figure 11
Most Utilized AI Algorithms by Process Type: Judgment Tasks
Source: Author's own elaboration.

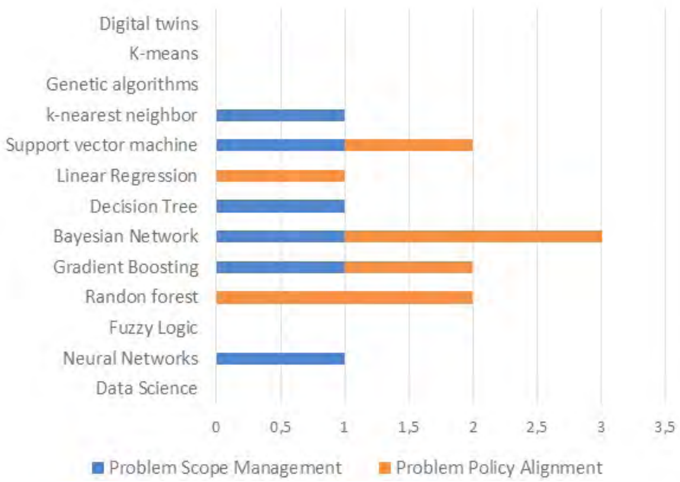

Figure 12
Most Utilized AI Algorithms by Process Type: Problem Tasks
Source: Author's own elaboration.

6. DISCUSSION

The discussion of the results from this literature review is structured around the four types of tasks where AI has been applied in OPM: repetitive or routine tasks, decision-making, judgment, and problem-solving. For each category, the literature's reported advancements are analyzed, considering the three OPM domains. As no contributions were identified regarding organizational enablers, this topic remains an open field for future AI applications.

6.1. AI Applications in Repetitive or Routine Tasks

In portfolio and program management, the most studied automation processes include information management and human resource allocation. Aligning information management with business objectives enhances project success and mitigates adverse impacts (Elkholosy *et al.*, 2022; Pantović *et al.*, 2024). Elkholosy *et al.* (2022) proposed a structured data acquisition model and an ML-based forecasting model to predict workforce requirements, improving project oversight. AI also enhances inter-project interactions; Zhang *et al.* (2024) developed an inter-project network based on graph neural networks and attention mechanisms to integrate project relationships dynamically. Yang *et al.* (2021) explored AI's role in agile program management, focusing on stage overlapping, shared resources, and knowledge transfer. Overall, AI enables data-driven decision-making, optimizes resource allocation, minimizes risks, and enhances adaptability in dynamic project environments.

AI has been applied across various PM process groups, including planning, execution, monitoring, control, and, to a lesser extent, project closure. In planning and execution, AI helps adjust parameters to predict outcomes and adapt to project environments. Studies have applied neural networks and variance analysis to forecast costs, timelines, and profit margins (Farouq, 2021; Ong & Uddin, 2020). Monte Carlo simulations have estimated budgets by assigning probabilities to costs (Wig & Martinez, 2019), while constraint-based algorithms have forecast project durations (Gil-Ruiz *et al.*, 2020). AI techniques, including fuzzy logic and historical data analysis, have improved cost budgeting and time projections (Auth *et al.*, 2021; Harish Kumar & Srinivas, 2024; Jaafar *et al.*, 2022). Automating cost and schedule processes enhances resource allocation, reduces errors, and improves timelines based on real-time data (Mohite *et al.*, 2023).

In monitoring and control, AI assesses progress and implements corrective actions. Real-time tracking enables stakeholders to review work details and track performance (Lordache & Marian, 2024). Big Data platforms and ML algorithms, such as linear regression, decision trees, and neural networks, optimize cost control (Almahameed & Bisharah, 2023; Chen, 2022; Indhujaa & Jaisankar, 2024). AI methodologies enable managers analyze deviations and make rescheduling decisions (Santos *et al.*, 2023). ML models, combined with Monte Carlo simulations, evaluate earned value metrics and predict shifts in execution timelines. At project closure, AI tools minimize waste, optimize resources, and improve decision-making efficiency (Hashfi & Raharjo, 2023).

AI significantly enhances PM by predicting outcomes and optimizing resources. Predictive analytics, utilizing gradient boosting and neighbor embedding, improves result accuracy and resource allocation (Babu *et al.*, 2024). AI-driven task assignments optimize human resource management (Elkholosy *et al.*, 2022), with workforce structure and size influencing project efficiency (Imeri & Imeri, 2024). However, challenges persist, including collection of inaccurate data, limited technical expertise, and reliance on data-driven decision-making. AI also enhances communication and document management. Natural language processing supports contract management and real-time document handling. AI-powered collaboration tools facilitate information sharing and streamline team communication, mitigating labor inefficiencies and human errors while improving stakeholder alignment (Chen *et al.*, 2021; Zabala-Vargas *et al.*, 2023).

6.2. AI Applications in Decision-making Tasks

In portfolio management, effective project selection should align with strategic objectives, managerial experience, and competitive factors while assessing risks to mitigate failures. Costantino *et al.* (2015) utilized artificial neural networks to improve project evaluation and risk analysis by linking success factors with key performance indicators and expert insights. Other methods include neural networks with entropy and analytic hierarchy processes for economic assessment (Bai *et al.*, 2022) and multicriteria analysis using genetic algorithms (Wang *et al.*, 2012) and particle swarm optimization (Rabbani *et al.*, 2010). Singh (2015) highlighted Big Data tools for planning and monitoring, reducing data overload, and classifying project success based on multiple criteria.

In PM, automating repetitive processes enables predictive and corrective analyses, providing essential data for decision-making. Auth *et al.* (2021) and Holzmann *et al.* (2022) highlighted the importance of AI tools in leveraging previous project data for planning and resource management. Si *et al.* (2023) applied digital twins to improve information analysis, data mining, state evaluation, and decision-making. Sommer (2024) introduced a five-level supervised decision model incorporating database construction and tool selection based on previous experience. Pantović *et al.* (2024) utilized historical data and performance metrics to assess strategies for business sustainability, integrating analytical techniques such as multiple linear regression. AI applications span all PM phases, including bidding, scheduling, quality control, cost estimation, and risk calculation (Hanjing *et al.*, 2022; Holzmann *et al.*, 2022). By integrating data-driven decisions, AI enhances adaptability and resilience in dynamic environments while reducing complexity, uncertainty, and risk interdependencies (Aamer *et al.*, 2024).

6.3. AI Applications in Judgment Tasks

Portfolio management evaluates risk, return, and project alignment with company objectives. Zaidouni *et al.* (2024) employed fuzzy factor analysis to predict portfolio risk based on historical data and expert input. Bilgin *et al.* (2022) developed a tool that integrates risk, return, and strategy, enabling contingency planning and alignment with corporate goals. Another key application is client management; Liu (2019) proposed a model based on fuzzy semantics and text mining to transform unstructured data into actionable insights, improving consumer behavior analysis and strategy development. These studies highlight the significant link between portfolio management and business strategy. However, AI applications in judgment-based tasks within program management remain limited, presenting opportunities for future research.

In PM, the initiation phase involves gathering key information for planning. AI-driven bid evaluation and probabilistic cost models help quantify risks and calculate bids (Gil-Ruiz *et al.*, 2020). Bayesian networks and vector models analyze historical project data complexity (Grabis *et al.*, 2019). AI also improves efficiency evaluation through neuro-fuzzy hybrid systems (Krichevsky *et al.*, 2019) and fuzzy logic for timeline estimation (Wig & Martinez, 2019). The node2vec algorithm aids in budgeting and task allocation (Mostofi *et al.*, 2024), optimizing resource planning by assessing risks and success rates (Hashfi & Raharjo, 2023).

Risk identification is crucial in PM. Timely and effective evaluation enhances project outcomes (Choi *et al.*, 2021; Mohite *et al.*, 2023). The Support Vector Machine algorithm predicts failures in software PM across 10 knowledge areas (Taye & Feleke, 2022). The Decision tree and Naïve Bayesian algorithms extract data to anticipate delays (Mohamad *et al.*, 2021). Real-time tracking of rejected requests with delay probabilities facilitate resource adjustments and scheduling corrections (Mohite *et al.*, 2023; Yang, 2024).

AI tools automate repetitive tasks and enhance risk analysis by processing large datasets. AI-driven prediction systems integrate with key PM process groups (Radhakrishnan & Jaurez, 2021). Studies show that AI adoption enables managers to detect risks early and implement mitigation strategies in dynamic environments where traditional tools prove insufficient (Mahdi *et al.*, 2021; Wei & Ding, 2022). AI insights help prevent overallocation or underutilization, improving resource allocation. However, challenges persist, including uncertainty, variability, and data quality, which are crucial for ensuring accurate PM predictions (Hashfi & Raharjo, 2023).

6.4. AI Applications in Problem-solving Tasks

In PM, the planning stage involves selecting methods and allocating resources. Kraiem *et al.* (2023) utilized ML-based tools to predict the most suitable PM method, identifying key variables via surveys and literature reviews. Merzouk *et al.* (2023) developed a model to determine the best management approach, focusing on Scrum, Scaled Agile Framework, and Dynamic Systems Development Method. Sakka *et al.* (2023) introduced a bottom-up decision analysis based on multicriteria evaluation to generate quantitative and qualitative insights. However, a key challenge remains: the availability of structured data. Other AI applications include commercialization and policy alignment. Jang (2022) applied ML models, such as logistic regression and random forest, to predict the commercial viability of research projects. Antony-Ranesh and Samuel (2022) applied Naïve Bayes to assess the alignment between government policies and project details, emphasizing the role of governance in project success. Overall, AI enhances method selection, commercialization, and compliance; however, data limitations pose challenges.

7. ORGANIZATIONAL CHALLENGES AND RESEARCH OPPORTUNITIES

This section discusses the results of the literature review addressing the second question posed. As mentioned earlier, AI applications in OPM have primarily focused on PM, with some advances in portfolio and program management. Most of the existing studies have mainly attempted to evaluate the predictive power of various algorithms. Literature synthesis (see Table 4) highlights the main organizational challenges and opportunities for future research, categorized into four main topics: 1) deficiencies in databases; 2) application of AI algorithms; 3) human management; and 4) ethical practices.

Table 4
Organizational Challenges and Opportunities for Future Research

Topics	Limitations	Challenges and Opportunities	References
Databases	Data inaccuracy	Create publicly accessible databases specifically designed for OPM to foster the development of AI tools Collect empirical, structured, and well-documented data focused on OPM to enhance the accuracy of analytical tools and improve the reliability of predictive models Develop advanced tools for data interpretation to transform large volumes of information	Auth *et al.* (2021); Babu *et al.* (2024); Bakici *et al.* (2023); Belharet *et al.* (2020); Choi *et al.* (2021); Elkholosy *et al.* (2022); Fridgeirsson *et al.* (2021); Guinhouya (2023); Harish Kumar & Srinivas (2024); Jaafar *et al.* (2022); Kim & Jang (2023); Li *et al.* (2021); Liu (2019); Liu & Hao (2021); Merzouk *et al.* (2023); Mishra *et al.* (2023); Müller & Klein (2020); Radhakrishnan & Jaurez (2021); Sommer (2024); Taye & Feleke (2022); Tereso *et al.* (2023) and Zhang *et al.* (2024).
Algorithms	Applications oriented to certain industrial sectors	Explore the effectiveness of AI tools across various industries and project types to identify patterns Develop customized algorithms tailored to the requirements of OPM domains and processes according to the industrial sector	Choquehuanca-Sánchez *et al.* (2024); Gil-Ruiz *et al.* (2020); Mahdi *et al.* (2021); Nenni *et al.* (2024); Radhakrishnan & Jaurez (2021); Taboada *et al.* (2023); Velezmoro-Abanto *et al.* (2024); Zabala-Vargas *et al.* (2023) and Zhang *et al.* (2024).
Human Management: Training and Skill Development	Insufficient AI and data analysis skills in project teams	Develop training programs for project teams focused on AI technologies and their applications in OPM Prepare the organizational structure and develop soft skills to minimize resistance to change and facilitate the successful implementation of AI technologies	Babu *et al.* (2024); Bahi *et al.* (2024); Bakici *et al.* (2023); Dam *et al.* (2019); Fridgeirsson *et al.* (2021); Gil-Ruiz *et al.* (2020); Müller *et al.* (2024); Nenni *et al.* (2024); Niederman (2021); Shang *et al.* (2023); Tominc *et al.* (2024) and Yang (2024).
Ethical Practices	Lack of specific ethical guidelines regarding AI applications in OPM	Develop ethical and legal frameworks that ensure data privacy and security in the implementation of AI in OPM	Babu *et al.* (2024); Bahi *et al.* (2024); Nenni *et al.* (2024); Yang (2024) and Zabala-Vargas *et al.* (2023).

7.1. Databases

The main deficiencies in databases for training algorithms pertain to availability, data quality, and inherent limitations of ML techniques. Databases such as MMLIB (Liu & Hao, 2021), COCOMO81, MAXWELL, China (Harish Kumar & Srinivas, 2024), Amazon2, Taobao3, and MIND_NEWS (Liu, 2019; Zhang *et al.*, 2024) are not sufficiently accurate for predictive applications. Mishra *et al.*, (2023) highlighted the challenge of accessing well-documented business data, while Choi *et al.* (2021) and Taye & Feleke (2022) indicated the scarcity of consistent data throughout the project lifecycle. Merzouk *et al.* (2023) emphasized the importance of collection models that account for project-specific limitations, such as in agile management and internet of things.

Furthermore, the lack of public and accepted databases limits the evaluation of PM approaches, impacting the effectiveness of AI algorithms, especially ML, which require comprehensive datasets for optimal performance (Auth *et al.*, 2021; Fridgeirsson *et al.*, 2021; Sommer, 2024). AI tools in OPM rely on accurate data, timely updates, and continuous adjustments (Belharet *et al.*, 2020). Data science and AI systems require frequent testing to detect errors and implement project-specific improvements (Radhakrishnan & Jaurez, 2021). Progress in OPM is sluggish because of the costs and time required to implement these technologies (Fridgeirsson *et al.*, 2021). ML techniques, despite their immense potential, experience significant challenges related to data quality and the need for robust infrastructure to manage voluminous data (Cinkusz *et al.*, 2024).

Rapid and effective data collection is crucial in OPM. The information modeling technology facilitates the extraction of valuable data from large volumes and their conversion into useful information utilizing specialized software (Li *et al.*, 2021). Elkholosy *et al.* (2022) developed a collection model; however, the paucity of training data affected accuracy. Many data points are obtained from project managers' recollections; other authors recommend case studies to capture empirical experiences instead of isolated interviews (Bakici *et al.*, 2023; Kim & Jang, 2023). Currently, databases are being created specifically for AI in PM, with voluntary contributions from organizations (Radhakrishnan & Jaurez, 2021). Predictive analysis will become increasingly important in OPM, driven by ML algorithms and evolving project data (Babu *et al.*, 2024).

This study could not identify any research that utilizing data specifically collected for this purpose. Data collection not only implies obtaining data; it also implies its effective application (Jaafar *et al.*, 2022). Project managers exhibit a greater willingness to employ AI systems that facilitate the interpretation and communication of collected data (Fridgeirsson *et al.*, 2021). However, a gap persists between data analysis tools and their application in PM, affecting decision-making and project progress (Alzeyani & Szabó, 2024; Guinhouya, 2023; Jaafar *et al.*, 2022; Tereso *et al.*, 2023). To address these challenges, innovative techniques are being developed, such as the utilization of social networks and AI systems that integrate narrative and electronic data, capturing real-time phenomena and accelerating the dissemination of results (Müller & Klein, 2020).

7.2. Algorithms

AI algorithms have limitations, which necessitates that project managers rely on their expertise to interpret results effectively (Gil-Ruiz *et al.*, 2020). This has driven the trend of integrating various AI tools into hybrid systems (Alzeyani & Szabó, 2024). Currently, autonomous PM systems do not fully consider the entire project environment, including client status, stakeholder involvement, and team performance (Gil-Ruiz *et al.*, 2020). Although a few companies have developed general AI algorithms, access to these remains limited (Radhakrishnan & Jaurez, 2021; Taboada *et al.*, 2023), and the sector's requirement for comprehensive technological models has yet to be fully addressed (Zabala-Vargas *et al.*, 2023). For future

AI developments in PM, several recommendations are suggested. Conducting case studies and pilot projects to validate in real-world contexts, and designing specific tools to integrate ML techniques into the industry. It is also crucial to create customized algorithms tailored to PM requirements (Velezmoro-Abanto *et al.*, 2024) and improve integration with existing PM systems, including intuitive interfaces that facilitate adoption. Additionally, optimizing the utilization of team feedback and incorporating external knowledge to offset the limited availability of data is recommended (Zhang *et al.*, 2024), along with managing stakeholders to reduce conflicts of opinion (Mahdi *et al.*, 2021).

7.3. Human Management: Training and Skill Acquisition

The exponential advancement of AI technologies has surpassed the learning curve of personnel in PM. Currently, professionals must acquire competencies in data science, access high-quality data, and adopt a data-driven approach in organizational decision-making (Babu *et al.*, 2024; Bahi *et al.*, 2024). However, AI implementation is challenging, primarily because of the high costs of infrastructure, training, and maintenance, limiting its adoption to large companies (Bakici *et al.*, 2023; Yang, 2024). Additionally, the lack of executive support and trained AI personnel complicates the process (Shang *et al.*, 2023). Overcoming these challenges requires continuous training efforts, stakeholder engagement, and investment strategies in security and skills for responsible and effective implementation (Nenni *et al.*, 2024).

Companies must have strong managerial backing, ensuring both adequate resources and employees trained in AI (Shang *et al.*, 2023; Tominc *et al.*, 2024). In addition to technical competencies, PM professionals must develop relevant soft skills. Cultural and generational impacts affect the perception and integration of AI, influencing managers' responsibilities, management processes, and interactions within the project (Müller *et al.*, 2024). Areas that require human leadership, empathy, and emotional intelligence will continue to demand human intervention, especially in managing human resources and stakeholders (Fridgeirsson *et al.*, 2021). Managers working with AI should adopt CRISP-DM interaction practices, as well as agile development methods, DevOps, etc., among other traditional approaches (Niederman, 2021). It will be crucial to define contextual frameworks that determine the level of autonomy in decision-making and data management (Müller *et al.*, 2024). While AI will optimize decisions and resources, the role of the project manager will evolve toward that of a data scientist, complementing the technology without replacing the human team (Gil-Ruiz *et al.*, 2020). Felicetti *et al.* (2024) recommended that to enhance the effective application of AI tools in PM, companies should implement specialized training programs and adopt explicit communication strategies that emphasize the direct benefits for task development in each project.

7.4. Ethical Practices

Finally, there are ethical concerns regarding data privacy and the potential for bias in predictive models. These concerns necessitate careful and responsible handling. Data security must be prioritized from the point of collection, ensuring that confidential information is not shared (Yang, 2024). It is essential to ensure that AI is utilized ethically, avoiding biases and adhering to privacy and security standards (Babu *et al.*, 2024; Bahi *et al.*, 2024). Appropriate management of data privacy and security, and training of personnel are key areas that must be addressed to maximize benefits and overcome limitations (Zabala-Vargas *et al.*, 2023). It is crucial to carefully review development contexts, the ethical and social implications of new strategies, and the potential risks of these technologies (Zabala-Vargas *et al.*, 2023). It is imperative that the tool meets data privacy and security standards (Nenni *et al.*, 2024).

8. CONCLUSIONS

The integration of OPM, encompassing program management, portfolio management, project management, and organizational enablers, is crucial for achieving an organization's strategic objectives. While AI has rapidly expanded in various sectors, this literature review highlights the need to extend its application within the realm of OPM. Recent findings indicate that AI has become increasingly valuable in OPM, particularly in automating repetitive tasks and supporting data-driven decision-making based on historical data. Research underscores that AI optimizes planning and estimation processes when reliable data is available. Moreover, applications such as digital assistants and intelligent management systems enhance efficiency, enabling managers to focus on collaborative and complex tasks.

In the context of OPM, the present literature review indicates that while most advancements in AI applications occur within the PM domain, progress has also been noted in program and portfolio management. However, they occur mainly in operational processes; the strategic aspects remain underdeveloped. Regarding organizational enablers, similar to the previously published review papers, no AI applications are reported. The processes most influenced by AI include cost, time, and human resource management, largely because of the availability of databases that enable the application of algorithms. However, challenges persist, such as insufficient data collection throughout the project lifecycle and the lack of algorithms capable of integrating different AI tools into hybrid system. Therefore, research opportunities are identified in developing specific platforms for data collection and creating customized algorithms tailored to the requirements of each project. Moreover, despite AI's advancements in the PM domain, most of the analyzed articles focus on projects in the financial and construction sectors, highlighting an open field for developing applications in other industries and service sectors.

8.1. Future Research Lines

Despite these PM advancements, program and portfolio management processes continue to lag. The literature also identifies opportunities to apply AI to organizational enablers, which are essential for supporting strategy development at the organizational level. Studies addressing organizational enablers or diffuse tasks —those involving multiple objectives and several possible outcomes— remain unexplored, presenting unique challenges. The requirement for empirical data collection and structuring to optimize AI applications in OPM is evident. While AI offers significant opportunities to streamline processes, a comprehensive approach encompassing both operational and strategic levels is essential to maximize its potential and ensure project success. The low success rates in projects suggest inadequate adaptation of PM practices to organizational specificities.

In this study, future lines of research were categorized into several topics. The main deficiencies in databases for training algorithms pertain to availability, data quality, and inherent limitations of ML techniques. AI algorithms have limitations, which necessitates that project managers rely on their expertise to interpret results effectively. The exponential advancement of AI technologies has surpassed the learning curve of personnel in PM. Ethical considerations include challenges in data privacy, customer perceptions of privacy breaches, security, and potential biases in AI systems.

This study opens new avenues for OPM research, particularly in applying AI to strategic areas such as portfolio and program management. Key research areas include creating public and well-structured databases, developing customized algorithms for OPM, training in AI technologies, and implementing ethical data handling practices. This study contributes to the understanding of AI in OPM, and emphasizes a holistic approach to enhancing strategic decision-making in organizations.

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