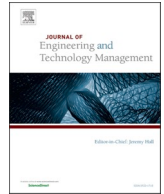




ELSEVIER

Contents lists available at ScienceDirect

# Journal of Engineering and Technology Management

journal homepage: [www.elsevier.com/locate/jengtecman](http://www.elsevier.com/locate/jengtecman)

## Beyond replacement: How project managers perceive the transformative role of AI in project work

Costanza Mariani <sup>\*</sup> , Mauro Mancini

Department of Management, Economics and Industrial Engineering, Politecnico di Milano Via Lambruschini, 4/B, Milano, MI 20156, Italy

### ARTICLE INFO

#### Keywords:

Artificial intelligence  
Project management  
Transformation

### ABSTRACT

Recent advancements in Artificial Intelligence (AI) have intensified discussions about job transformation, with growing evidence that many professional roles will be significantly affected. This paper examines the impact of analytical AI systems on project management, focusing on how data-driven, algorithmic tools influence both the quantitative and qualitative dimensions of project management activities. While existing studies often highlight the potential of AI in this domain, they frequently concentrate on generative AI or overlook project managers' own expectations regarding whether analytical AI will replace or augment their work. Using the Nominal Group Technique, this study investigates which project management activities practitioners expect to be replaced, supported, or remain unaffected by analytical AI. The findings reveal that although analytical AI is not anticipated to replace project managers, it is likely to reshape how tasks are executed. As a result, project managers will increasingly need to develop new skills and competencies to remain competitive in an AI-enhanced project environment.

### 1. Introduction

Back in 1821, at the height of the First Industrial Revolution, David Ricardo, one of the most influential classical economists of the early 1800s, published the third and final version of his most important work, "Principles of Political Economy and Taxation." Compared with the previous two editions (the first published in 1817), the content of the book had remained virtually unchanged except for a new chapter on the automation of labor, titled "On Machinery." In this chapter the London economist anticipates the concept of "technological unemployment" (officially theorized by Keynes in 1930), expressing his concern about the possible destructive effects on employment of the introduction of machinery. Since then, the topic of the effect of innovative forms of automation on jobs and employment has resonated throughout the entire history of political economy: Marx put technological change, the ownership of machinery and organizational structure at the core of his critique of capitalism, while on the contrary Schumpeter theorizes the concept of "creative destruction", pointing out that economic growth occurs through the introduction of innovation that inevitably destroys previous organizational forms, jobs and skills while generating new capital. Although these subjects are not new, the advent of emerging technologies, such as Artificial Intelligence (AI), has created a new emphasis on the topic, drawing attention back to the possible job transformation that could be generated by the implementation of AI in the actual job market.

In fact, some authors stress the risk that the introduction of these new technologies could have in replacing humans in performing their actual tasks. For example Frey and Osborne (2017) points out that jobs will be highly susceptible to automation by AI and other

\* Corresponding author.

E-mail addresses: [Costanza.Mariani@polimi.it](mailto:Costanza.Mariani@polimi.it) (C. Mariani), [Mauro.Mancini@polimi.it](mailto:Mauro.Mancini@polimi.it) (M. Mancini).

<https://doi.org/10.1016/j.jengtecman.2025.101927>

Received 16 January 2024; Received in revised form 24 November 2025; Accepted 24 November 2025

Available online 28 November 2025

0923-4748/© 2025 Elsevier B.V. All rights reserved, including those for text and data mining, AI training, and similar technologies.

digital technologies with around the 47 % of them at risk of being replaced relatively soon, probably over the next decade or two; [Acemoglu and Restrepo \(2020\)](#) highlights that in the US market, each additional robot per thousand workers theoretically reduces the local employment-to-population ratio by 0.39 %age points and wages by about 0.77 %; moreover, there is an increasing number of cases in both the services and public sector industries of integrated applications of innovative digital technologies, machine learning and AI techniques affecting middle-skill, white-collar occupations including legal services, data operations, medical and customer services and public services delivery ([Clifton, Glasmeier and Gray, 2020](#)). [Chui, Manyika and Miremadi \(2016\)](#) suggest that, although AI may not fully automate entire jobs, it has the potential to automate up to 45 % of tasks across both low-skill and high-skill professions. While numerous studies have extensively analyzed the implications of AI on employment, particularly in sectors such as manufacturing ([Chiarini et al., 2024](#)), finance ([Wang et al., 2023](#)), customer service ([Leocádio et al., 2024](#)) and accounting ([Rawashdeh, 2025](#)) a growing body of research is now examining its effects on knowledge-intensive and managerial roles. For example, ([Susskind and Susskind, 2015](#)) discuss how AI is reshaping the roles of financial analysts, consulting professionals, and even legal professionals by automating cognitive tasks. Similarly, [Hunt, Sarkar and Warhurst, \(2022\)](#) investigate how AI capabilities are increasingly overlapping with tasks requiring medium to high cognitive load also in the public and governmental sector in activities such as strategic decision-making and complex analysis. However, despite this growing literature, project management remains a relatively under-investigated domain. Most existing studies on AI in project management focus on tools and applications supporting technical processes—such as scheduling, risk modeling, or cost forecasting ([Ruiz, Torres and Crespo, 2020](#); [Khatib, Zitar and Al-Nakeeb, 2021](#))—without considering the broader implications for the project manager's role as a whole. Some studies on the adoption of AI in project management indicate that these advanced technologies are more frequently adopted in repetitive and quantitative-based processes ([Adel Belharet, 2020](#); [Fridgeirsson et al., 2021](#); [Holzmann, Zitter and Peshkess, 2022](#); [Mariani and Mancini, 2023](#)). However, they pose challenges when applied to qualitative contexts and the management of soft skills ([Bodea, Mitea and Stanciu, 2020](#); [Davahli, 2020](#)). These studies provide a preliminary understanding of AI's potential applications in project management, yet they do not fully address the crucial issue of how project managers perceive these technologies as potential replacements for their jobs. Additionally, they overlook the transformative impact AI could have on the nature of the tasks. This gap is particularly critical, given that project managers operate at the intersection of strategic planning, cross-functional coordination, and human leadership—areas where the integration of AI could lead both to task automation and to a profound role transformation ([Poba-Nzaou et al., 2021](#)). Understanding how project managers themselves perceive these changes for their profession is relevant to designing appropriate upskilling strategies and guiding policy and organizational responses ([Long and Magerko, 2020](#); [Ng et al., 2021](#)). Moreover, exploring their views enables a more grounded understanding of AI's organizational impact, moving beyond technical feasibility toward a more human-centered and professional perspective. In light of the need for additional exploration to gain insights into how project managers perceive the role of AI in their profession, and whether they view it as a substitute or complement to their project management skills, this study aims to answer the following research question:

*RQ: According to project managers, which project management activities are likely to be substituted, transformed, or remain unaffected by AI?*

As the trend of projectification continues to rise, transforming projects into a distinct form of business organization ([Jensen, Thuesen and Gerdali, 2016](#)), ([Schooper and Ingason, 2019](#)), there is a growing need to explore how innovative techniques, such as AI, are likely to replace or transform the processes and activities performed for delivering projects ([Holzmann, Zitter and Peshkess, 2022](#); [Müller et al., 2024](#)). To address our research question, we conducted an exploratory study involving 32 experienced project managers from five different industries across six European countries: Italy, Austria, Slovenia, Croatia, Germany, and Serbia. Given the novelty of this domain for both researchers and practitioners, their perspectives were gathered through the Nominal Group Technique (NGT) ([McMillan et al., 2014](#)), a structured method for focused discussion aimed at identifying activities that are likely to be replaced, transformed, or remain unchanged by AI. This method ensures a systematic exploration of diverse perspectives within the sample of interviewed project managers, contributing to a complete understanding of AI's evolving role in project-related tasks. The primary goal of this study is to examine the potential impact of AI systems and applications on the role of project managers from the perspective of industry professionals, capturing their expectations on how AI might shape their profession in the future. The paper begins with a concise review of what is AI and how it is expected to transform job roles and tasks, followed by a review of the literature on its integration into project management activities. The subsequent section details the utilization of the two-round NGT to gather consensus from a diverse group of experienced project managers. The discussion section involves interpreting the results and addressing additional insights that emerged during the study. Finally, the article concludes by summarizing the theoretical and practical implications, acknowledging research limitations, and proposing directions for future studies.

## 2. Background

### 2.1. Defining artificial intelligence

While AI is often seen as a cutting-edge technology, its roots date back several decades. In 1950, Alan Turing formally defined AI as the ability of a machine to display intelligence in a way that a human observer could not distinguish its behavior from that of a person ([Turing, 1950](#)). Since that time, AI has undergone varying phases of popularity and interest. These fluctuations are a result of significant advancements in innovative technologies and algorithms, coupled with disparities between expectations and actual outcomes and applications in practice ([Haenlein and Kaplan, 2019](#)). The extant literature provides diverse definitions of AI which are based on (a) the extent of the system's application intent, which allows distinguishing between narrow (systems designed to perform specific tasks) and general (systems aiming to replicate human-like intelligence across a wide range of activities) AI, and (b) the stage of the

system's development and use, which includes research, design, development, deployment, and utilization (Unesco, 2023). We will adopt a common yet very clear definition of AI as "systems that display intelligent behavior by analyzing their environment and taking actions - with some degree of autonomy - to achieve specific goals" (European Commission, 2020). This definition encompasses various AI techniques, such as machine learning, natural language processing, computer vision, and robotics, all of which enable systems to interpret data, learn from it, and make decisions autonomously (Borges et al., 2021). More recently, it has become increasingly important to distinguish between different typologies of AI, especially in applied contexts. Among the most prominent categories are Generative AI—systems such as large language models and image generators that create new content based on learned patterns—and Analytical or Predictive AI, which focuses on recognizing patterns in data, generating forecasts, or supporting complex decision-making processes (Feuerriegel et al., 2024). A third emerging category includes Agentic AI, which refers to systems capable of autonomous action and interaction within defined environments (Acharya, Kuppan and Divya, 2025). These typologies differ both for their technological architectures and for their levels of autonomy, use cases, and implications for human-AI collaboration. In the context of this study, we explicitly focus on Analytical AI, meaning those systems that use machine learning, statistical modeling, or optimization algorithms to analyze data and support managerial tasks such as forecasting, monitoring, prioritization, and resource allocation. Our empirical investigation and research design were intentionally framed around this typology, as it currently represents the most common and accessible class of AI tools being considered or implemented by project professionals in their day-to-day work (Nilsson, 2023; Müller et al., 2024). More specifically, our focus is on those technological capabilities that enable AI systems to process information intelligently and autonomously, thus performing activities that are currently integral to human project management tasks, particularly those that are data-intensive or repetitive in nature (Chui, Manyika and Miremadi, 2016; Manyika, 2017).

## 2.2. The impact of AI on jobs

Although there are different perspectives about the extent the impact of AI will have on jobs, the literature agrees that it will be inhomogeneous over different countries, industries, and jobs. In terms of differences in the level of AI diffusion in different regions, it seems to be clear that place matters. For instance, activities replacement driven by AI tends to occur more rapidly in industrialized regions—where manufacturing sectors dominate and processes are more easily automated (Kinkel, Baumgartner and Cherubini, 2022; Chiarini et al., 2024). Conversely, regions with a higher concentration of service-based industries may adopt AI more cautiously or in support roles (Clifton, Glasmeier and Gray, 2020; Poba-Nzaou et al., 2021). Similarly, organizational work culture also has an impact (Waldman-brown, 2020) as well as regulatory structures; for example, in the European Union, strict frameworks such as the General Data Protection Regulation (GDPR) (European Commission, 2016) or the EU AI Act (European Commission, 2024) impose clear limitations on algorithmic decision-making and the processing of employee data, having an impact on AI adoption in fields like HR or internal project analytics. Similarly, differences in intellectual property protections, such as between the EU and the US (Wojan, 2019), can influence the extent to which AI-generated outputs are integrated into project deliverables or knowledge management systems. In this sense in more strict regulatory frameworks like the EU the interpretations of authorship and ownership rights affects how confidently organizations adopt AI-generated content in project outputs or knowledge repositories. (Campi and Dueñas, 2019; Nemioglu, 2019). However, the impact AI can have on job transformation depends also heavily on the type and content of the job. Fossen and Sorgner (2019) point out that for some occupations the risk of a total replacement of human work by AI is very high, implying a destructive effect of the introduction of these new technologies on the job market; on the other hand other authors give evidence of a transformative effects, meaning that for some occupations AI will still bring substantial changes in the activities and skill requirements, but machines will not substitute the human workers (Brynjolfsson and McAfee, 2014; Felten, Raj and Seamans, 2018). Some scholars contend that the introduction of AI may not lead to a purely destructive or transformative impact on occupations. Rather, they argue that the degree of impact varies gradually based on the specifics of job content and industry. For example, Fossen and Sorgner (2019) categorize occupations by their susceptibility to AI impact into four clusters on a two-dimensional chart. "Rising stars" are minimally impacted by AI, with some changes in processes and work division but no threat to human jobs. "Machine terrain" occupations face significant transformative and destructive impacts, where both processes and job content are radically changed, potentially making human roles obsolete. "Human terrain" includes jobs unlikely to be replaced due to competencies that AI cannot yet replicate. Lastly, the "collapsing" cluster represents jobs at high risk of full automation. The literature regarding the impacts of AI on jobs and occupations presents some interesting analysis and results, however, there remain some areas only marginally covered. In particular, (i) the literature focuses predominantly on the study of the *destructive effects* (Frey and Osborne, 2017a), (Arntz, Gregory and Zierahn, 2016a), (Pajarinen, Rouvinen and Ekeland, 2015) and on the generation of new occupations (Degryse, 2016) and explores only marginally (Bessen, 2016), (Autor and Dorn, 2013) the implications of the *transformative effects* of AI on existing jobs and occupations; some papers generally examine the impact of AI on project management activities (Fridgeirsson, 2016; Holzmann, Zitter and Peshkess, 2022) but (ii) to the best of the authors' knowledge, there are no papers that examine the spectrum of AI's impact, ranging from complete replacement of task execution by AI, to support that may lead to a transformation in how an activity is performed, up to no impact at all.

Further, the firm level literature on the integration of AI into the workplace primarily takes a political-economic perspective, focusing on analyzing either the detrimental or transformative effects on various occupations on markets. This discourse is dominated by studies such as those by Frey and Osborne (2017), and Acemoglu and Restrepo (2020), which extensively discuss AI's broader impacts on the labor market. Despite the value of these insights, the literature significantly overlooks the managerial implications of adopting these emerging technologies. There is a lack of attention on how AI reshapes internal organizational dynamics and job roles. This gap is particularly relevant for project managers, who operate within organizations—both project-based and process-oriented—where AI-driven transformations at the firm level directly affect their roles, responsibilities, and required competencies.

### 2.3. The impact of AI on the project management role

Recent literature unanimously underscores the scarcity of reported cases regarding empirical applications of AI in project management. This dearth of practical examples complicates the accurate extrapolation of the extent to which AI might replace or transform activities related to project management in the coming years (Fridgeirsson et al., 2021; Holzmann, Zitter and Peshkess, 2022). The absence of empirical studies makes it challenging to formulate precise predictions concerning the degree to which AI could influence and reshape project management as a profession. However, by reviewing the literature on AI applications in project management, it is possible to identify recurring patterns and trends in the areas where scholars have conducted more research proposing AI applications to PM. These trends suggest that these areas are those where the technical feasibility of application is most pronounced, making them potentially replaceable by AI. The first point that emerges from the literature is that the uses of AI in project management have mostly been reported in the context of quantitative activities. For example, the risk management processes are widely covered: according to (Pan & Zhang, 2021), various AI methods, such as machine learning, and neural networks are employed to replace traditional risk analysis methods, which rely on the judgment of human experts to identify potential risks and assess their severity, solving related problems such as vagueness and the risk of errors caused by subjective judgment. In this sense some authors have highlighted the benefits AI can have on risks' assessment and identification (Mancini, Mariani and Manfredi, 2023; Mariani and Mancini, 2023) and to its management (Wang and Jin, 2019), AI is also employed in papers regarding the field of project budgeting, where its primary applications include forecasting both the magnitude and timing of incoming cash flows (Mariani et al., 2025) as well as performing conceptual cost forecasting (Flyvbjerg et al., 2022; Inan, Narbaev and Hazir, 2022) with the aim of facilitating precise cost estimations during the initial stages of a project. At the same time also in project scheduling (Bahroun et al., 2023) together with effort estimation (Kassaymeh et al., 2024) the effectiveness of diverse machine learning algorithms, such as K-Nearest Neighbors (KNN), multiple linear regression, and Support Vector Machine (SVM), are assessed and compared in order to be employed for estimating the necessary resource effort for particular project tasks. In addition to this, AI has also been employed to optimize the allocation of resources and to improve the control of project progress and quality during execution (Rankovic et al., 2024). AI can aid in calculating and forecasting the Estimation at Completion (EAC) indicator as in Kamoona and Budayan (2019) where Neural Networks and Support Vector Machine algorithms are employed for forecasting the value of this indicator during the early projects' phases so to be able to implement immediate corrective actions. At the same way, Balali et al. (2020) employ an ANN and multiple regression in order to predict project cost indices during project progress more accurately and based on ongoing data, while other papers suggest employing anomaly detection algorithms (Dong et al., 2025) or integrated control systems for early detection of deviations from project baselines (Azharuddin et al., 2022), however, in general, papers advocating the use of AI throughout a project's lifecycle have the dual purposes of predicting predefined performance metrics like project time and cost and implementing control dashboards that monitor predictively project progress. This, in turn, enables proactive action planning and timely responses by project managers (Flyvbjerg et al., 2022). A survey conducted by (Nilsson, 2023) reports that AI systems that tracks projects' performances and forecast project outcomes, are among the currently most used tools employed in project management activities. This is also true in infrastructure projects' sites where a massive amount of generally unstructured photos, videos, and other types of data (like reports, real-time equipment, and site monitoring) can be produced nowadays (Prasad et al., 2024) to be subsequently aggregated and analysed with advanced AI techniques both to optimize site performance, but also to detect potential safety hazards, such as workers not wearing appropriate safety equipment or equipment operating in unsafe conditions (Pan and Zhang, 2021). All the reported activities are quantitative based, and consequently easier to automate and analyze in computerized systems that operates predominantly through rules and algorithms. Moreover, certain tasks, such as scheduling and resource allocation, exhibit the repetitive nature, since they are often carried out multiple times within the same project. These aspects point to the hypothesis that AI could only have an impact on the project manager's profession with regard to repetitive and automatable tasks, while the more qualitative and strategic ones will remain in the control of project managers (Auth, Jokisch and Dürk, 2019; Fridgeirsson et al., 2021; Holzmann, Zitter and Peshkess, 2022). Nevertheless, more recent publications appear to indicate potential influences on tasks of a more qualitative nature, suggesting a supportive role for AI rather than the outright replacement of humans, as projected for quantitative tasks. For example, some authors report that AI can be adopted in the procurement phases, to manage contract negotiations and disputes (Kiani, 2024) but also in project portfolio selection (Sánchez-Fernández, Díez-González and Perez, 2025) and project knowledge management (Nenni et al., 2025) as well as in stakeholder classification (Mariani, Navrotska and Mancini, 2023). The fact that AI applications are expanding into more qualitative aspects of project management tasks specifically heightens interest in examining how AI can potentially transform these activities.

## 3. Research design and methodology

### 3.1. Identification of the research problem

After conducting the literature review, it became evident that a gap exists in the current body of knowledge concerning the potential applications of AI in the field of project management. One facet of the literature underscores the role that recent advancements in AI technologies can play in managerial contexts, encompassing both operational (Tariq, Poulin and Abonamah, 2021; Zhang and Lu, 2021) and strategic activities (Borges et al., 2021). Conversely, in the project management field, the literature suggests the technological feasibility of incorporating these advancements, with project managers anticipating their imminent application in their tasks (Bodea et al., 2020). Nonetheless, the absence of empirical studies on organizational implications hinders the evaluation of the substitutability degree of these technologies in the activities carried out by project managers. The literature regarding the degree of

substitution (from complete replacement, transformation or not impacted) of these technologies for human-based activities and its impact on the profession under consideration relies heavily on the nature of the tasks performed. As previously mentioned, Fossen and Sorgner (2019) categorize professions into four clusters – "rising stars," "machine terrain," "human terrain," and "collapsing" – depending on the varying degrees of substitutability of human tasks by AI. Our study is exploratory in nature, as it addresses the limited empirical evidence currently available on how AI affects specific project management tasks (Waters, 2007). This approach enables us to identify emerging patterns and generate insights to inform future research (Stebbins, 2001). Our study concentrates on the principal

**Table 1**

List of the knowledge areas and activities (adapted from the PMBoK 6th Edition) employed as input in the Nominal Group Technique.

Knowledge Area	Activity	Description
1. Project Integration Management	1. Developing and updating the project charter	Creating and maintaining the project charter, outlining the project's objectives, stakeholders, and overall scope.
	2. Monitoring Project progress and making adjustments as necessary	Constantly tracking project advancements, this activity requires making necessary adjustments to ensure alignment with project goals and timelines.
	3. Performing integrated change control	Managing changes to project scope, schedule, and costs, ensuring that modifications are properly evaluated, approved, and implemented.
2. Project Scope Management	4. Defining Project scope	Establishing the clear and detailed parameters of the project, including objectives, deliverables, constraints, and acceptance criteria.
	5. Creating the WBS	Developing the Work Breakdown Structure, a hierarchical decomposition of the total scope into manageable work packages, aiding in project planning and control.
	6. Monitoring Project scope	Regularly assessing and verifying that project activities align with the defined scope, making adjustments as needed.
3. Project Schedule Management	7. Defining and sequencing Project activities	Identifying and organizing project activities in a logical order, facilitating efficient execution and resource allocation.
	8. Estimating activities resources and duration	Determining the necessary resources and time required for each project activity, aiding in project planning and resource management.
	9. Developing the Project schedule	Creating a detailed project schedule that outlines the sequence and duration of project activities.
	10. Monitoring the Project schedule	Continuously overseeing the project schedule, making adjustments to ensure adherence to timelines and identifying potential delays.
4. Project Cost Management	11. Estimating Project costs	Predicting the financial requirements for the project based on the scope, resources, and duration of activities.
	12. Monitoring Project costs and cash flows	Regularly tracking project expenditures and cash flows, ensuring financial alignment with the project budget.
5. Project Quality Management	13. Identifying Project quality requirements	Defining the standards and expectations for project deliverables to meet quality objectives.
	14. Monitoring Project quality standards	Continuously evaluating project deliverables to ensure they meet the established quality standards.
6. Project Resource Management	15. Identifying necessary project resources	Determining the human, material, and equipment resources required for project success.
	16. Monitoring Project resources availability and saturation	Regularly assessing the availability and capacity of project resources, ensuring optimal utilization.
7. Project Communication Management	17. Communicating Project status and progress to stakeholders	Keeping stakeholders informed about project developments, milestones, and any potential issues.
	18. Managing communications within Project team	Facilitating effective communication among project team members to ensure collaboration and information flow.
8. Project Risk Management	19. Identifying Project risks	Recognizing potential risks that could impact project success, encompassing various aspects such as scope, schedule, and resources.
	20. Prioritizing Project risks by assigning probability of occurrence	Assessing and ranking project risks based on their likelihood of occurring.
	21. Performing Project Risk responses	Developing and implementing strategies to mitigate or respond to identified project risks.
9. Project Procurement Management	22. Identifying Project Procurement needs	Recognizing the goods and services required for the project and initiating the procurement process.
	23. Selecting suppliers	Evaluating and choosing suppliers based on criteria such as quality, cost, and reliability.
	24. Managing contracts with suppliers	Overseeing and ensuring compliance with contractual agreements with project suppliers.
10. Project Stakeholder Management	25. Identifying and analyzing project stakeholders	Identifying individuals or groups with an interest in or impact on the project and analyzing their influence.
	26. Monitoring and engaging stakeholders	Continuously tracking stakeholder interests and involvement, actively engaging them throughout the project.
11. Leadership and Team Management	27. Assigning tasks and responsibilities to team members	Allocating specific duties and roles to project team members based on their skills and expertise.
	28. Monitoring team members' performance and providing feedback	Regularly assessing the performance of team members, providing constructive feedback, and addressing issues.
	29. Coaching, leading and motivating the Project team	Providing guidance, leadership, and motivation to ensure a high-performing and cohesive project team.
	30. Making decisions and solving conflicts as they arise	Taking decisive actions and addressing conflicts promptly to maintain project momentum and harmony within the team.

activities of project management. Through the insights of 32 experienced project managers, it seeks to prioritize responses to the question of which project management tasks will be completely replaced by AI, which will be transformed by AI, and which will remain unaffected by AI. The novelty of our paper lies in its exploration of the predicted impacts in terms of complete replacement and transformation, allowing for a more nuanced view of AI's prospective impacts. This perspective is crucial as it provides a nuanced view of how AI is expected to impact project management, identifying which tasks may be automated soon and which will likely require human skills longer, thereby guiding strategic planning for future project management practices. Conducted as an exploratory study, the present research intentionally refrained from defining a closed list of specific AI techniques for voting, as such delineation could have restricted responses from project managers. However, through an initial discussion during the in-presence workshop, it was decided to adopt a definition of AI as 'systems that display intelligent behavior by analyzing their environment and taking actions—with some degree of autonomy—to achieve specific goals.' Following this, we collectively discussed the main AI techniques currently in use. This approach helped to ensure that the study remained open and flexible, allowing participants to share their experiences and insights based on a broad understanding of AI, rather than limiting them to a predefined set of technologies. On the other hand, in order to attain a structured overview of how AI could potentially alter project management activities, we chose to use a slightly modified version of the categorization of activities outlined in the 6th Edition of the PMBoK (PMI, 2017). During an introductory in-person workshop with participants, these knowledge areas were identified as a familiar and accessible framework for categorizing core project management tasks. Nonetheless, during the discussion, participants noted that the 'Resource Management' section of the PMBoK encompassed two conceptually distinct areas: 'Estimate Resource Requirements' and 'Acquire and Release Resources,' which are largely quantitative-based and administrative, and 'Develop Team,' 'Manage Team,' and 'Control Team,' which are based on motivational theories and leadership principles, such as Motivation Theory, McGregor's Theory of X and Y and Maslow's theory of primary needs (PMI, 2017). In a collective process of consensus building, participants agreed that given the increasing relevance of AI's application to leadership tasks—as previously discussed in the background section—it was appropriate to dedicate a separate area to 'Leadership and Team Management' activities in the NGT group input for discussion. In the same workshop, with the support of the selected project managers, 30 fundamental activities were selected to be prioritized in the subsequent Nominal Group Technique's workshops. The list of knowledge areas employed, the selected activities, and a brief description of each of them are presented in Table 1.

### 3.2. 3.2 Method: qualitative nominal group technique (NGT)

The Nominal Group Technique (NGT) stands out as one of the most frequently utilized formal methods for consensus development. This approach is employed to gather expert opinions on a specific topic, facilitating group consensus through structured face-to-face workshops (Harvey and Holmes, 2012; McMillan, King and Tully, 2016). NGT is thus usually employed for prompting responses from each group member to predetermined, structured questions. Some scholars contend that this enhances the efficacy of focus groups as information sources by generating data on a specific topic or question and prioritizing problems and issues through group discussion (Langford, Schoenfeld and Izzo, 2002). This technique typically involves three distinct phases. In the first phase, one to two questions are sent to participants in advance to encourage reflection on the topic. In the second phase, during the workshop, the facilitator guides participants in a 'round robin' fashion, where each participant shares a single idea with the group, allowing for the emergence of new ideas. The facilitator records the results verbatim on a flipchart or whiteboard. The third stage involves clarification and classification, where, after clarifying the provided ideas, participants are tasked with ranking them according to a predefined Likert scale (McMillan et al., 2014), (Denning, Jones and Sampson, 2013). Despite this being considered the standard process, NGT is a highly adaptable method. In the case of this paper, we followed the indication provided by (McMillan, King and Tully, 2016) where it is suggested that ". NGT can be tailored to align with the research purpose, participant availability, the required level of clarification, and the most suitable method for consensus or generalizability needed for the topic". The variations to NGT employed in our research design, integrates some of the diversification which are seen as most common in literature: (i) during the "generating ideas" phase, rather than employing silent generation followed by a round robin, the knowledge areas to be assessed were extracted from the literature, specifically from the PMBoK (PMI, 2017) and validated by participants. This is considered common in the application of the method, as reported by (Hilgsmann et al., 2013) (ii) due to limited time during the first workshop, the re-ranking happened via a secondary survey, following the methodological guidelines provided by (Allen, Dyas and Jones, 2004). The literature has sometimes highlighted limitations of the NGT methods such as (i) the potential influence of group dynamics on individual responses, as participants may be swayed by the opinions of others, (ii) the overly structured nature of the process that may limit the exploration of more spontaneous ideas that could arise in a less formal setting and (iii) the assumption of equal participation and contribution from all group members, which might lead to overlooking the expertise or insights of more silent individuals (Gallagher et al., 1993; Mullen et al., 2021). Nevertheless, we chose to employ this method for several reasons. Firstly, adopting a qualitative research approach that, as NGT, is grounded in the insights of experienced project managers, guided by a critical interpretive perspective, holds the potential to unveil novel perspectives on complex avenues of research in project management (Cicmil, 2006). Secondly, focusing specifically on this technique, it has been recurrently utilized to comprehend the priorities of users within specific professional categories regarding innovative topics such as AI (Musbahi et al., 2021) or machine learning (Naudé and Bornman, 2021). Therefore, it can provide a valid method for addressing the novel research question of this study. Lastly, literature reports that the ability to achieve consensus through direct comparison among group members encourages thoughtful reflection and facilitates the collective identification and ranking of crucial factors (Allen, Dyas and Jones, 2004; Mullen et al., 2021), thus representing a valid tool for examining which project management activities are most at risk to be substituted by AI. In the following section we will outline in detail the expert panel selection and the research steps followed in the analysis.

**Table 2**  
Participants list and key information.

# Participant	Role	Job Title	PM Experience [years]	AI Expertise	Age	Gender	Nationality	Industry
1	Project Manager	Project Engineering Manager	10–15	Intermediate	35	M	IT	IN
2	Project Manager	Partner Success Project Manager	10–15	Intermediate	32	F	AT	FB
3	Project Manager	Site Project Manager	10–15	Basic	32	M	HR	IN
4	Project Manager	Site Project Manager	10–15	Basic	33	M	HR	IN
5	Project Manager	Project Engineering Manager	10–15	Advanced	31	F	AT	PB
6	Project Manager	Process Project Manager	10–15	Intermediate	33	M	IT	AT
7	Project Manager	Lab Project Manager	10–15	Intermediate	34	F	AT	PB
8	Project Manager	Risk Project Manager	10–15	Intermediate	36	M	HR	IN
9	Program Manager	Program Manager	10–15	Intermediate	38	F	AT	PB
10	Program Manager	Senior Consultant	10–15	Intermediate	35	F	AT	CS
11	Program Manager	Project Operations Manager	10–15	Intermediate	35	F	IT	FB
12	Project Manager	Project Manager	10–15	Intermediate	34	F	AT	FB
13	Program Manager	Director	10–15	Basic	38	F	DE	FB
14	Program Manager	Program Manager	10–15	Advanced	39	M	IT	AT
15	Portfolio Manager	Director	15–20	Intermediate	40	F	HR	CS
16	Program Manager	Technical Program Manager	15–20	Advanced	42	M	IT	AT
17	Program Manager	Program Manager	15–20	Basic	40	M	HR	IN
18	Project Manager	Site Project Manager	15–20	Intermediate	41	M	SL	IN
19	Project Manager	Document Project Manager	15–20	Intermediate	41	F	IT	PB
20	Project Manager	Project and Product Manager	15–20	Intermediate	40	M	IT	PB
21	Project Manager	Project Manager	15–20	Intermediate	43	F	SL	CS
22	Project Manager	Internet and Mobile Project Manager	15–20	Intermediate	40	F	SL	FB
23	Project Manager	Project and Product Manager	20–25	Intermediate	48	F	SL	FB
24	Project Manager	Site Project Manager	20–25	Basic	54	M	IT	IN
25	Project Manager	Project Manager	20–25	Basic	52	M	IT	FB
26	Portfolio Manager	Partner	20–25	Basic	56	F	SL	CS
27	Project Manager	Project and Product Manager	05–10	Intermediate	30	M	SL	PB
28	Project Manager	Senior Consultant	05–10	Intermediate	29	M	SL	CS
29	Project Manager	Technical Project Manager	05–10	Intermediate	28	M	IT	FB
30	Project Manager	Senior Consultant	05–10	Advanced	28	F	RS	CS
31	Program Manager	Program Manager	05–10	Intermediate	29	M	IT	FB
32	Project Manager	Risk Project Manager	05–10	Intermediate	31	M	RS	IN

3.3. Panel selection

The participants were selected using a snowball sampling method, as the Nominal Group Technique does not necessitate to select a sample representative of the entire population in a statistical sense (Gallagher et al., 1993). Nevertheless, since the primary objective of these studies was to gather information from highly experienced project managers, we chose a sample of professionals in project management with a minimum of 5 years of work experience. The research population included 32 project professionals, predominantly Project Managers, from companies across five diverse industries: "Consultancy" (CS), "Pharma & Biotech" (PB), "Industrial Technologies, Infrastructure and Automation" (IN), "Fintech & Banking" (FB), and "Automotive" (AT). To enhance the generalizability of our findings, our sample included 11 project professionals from Italy (IT), 5 from Croatia (HR), 6 from Austria (AT), 7 from Slovenia (SI), 1 from Germany (DE), and 2 from Serbia (RS). Table 2 provides a summary of key information characterizing the 32 respondents, including their demographic information, roles, project management experience, industry affiliation, and job title.

The decision to include Project Managers from different sectors and with diverse roles and age groups was intentional, as it allowed for a more comprehensive understanding of how adopting AI could impact PM activities across multiple organisational contexts and industries. The literature highlights that a participant range of 7–14 is suitable for a Nominal Group (McMillan, King and Tully, 2016); however, due to the presence of two facilitators during the workshop, it was decided to expand the sample to gather a greater number of responses and enhance the robustness of the results. The participants are from different countries around Europe, 17 of them are male and 15 females; the average age is 37.41 years. The majority of participants, around 62.5 %, have 10–15 years of experience, followed by 28.1 % with 15–20 years, and 9.4 % with 20–25 years of experience; Regarding their role the 71.88 % of participants were Project Managers, the 25 % Program Managers, and the 3.13 % Portfolio Managers. In accordance with the recommendations of Gallagher et al. (1993) the chosen participants were impartial and unbiased. In our selection process, we established specific criteria to ensure that: (i) geographical diversity was maintained; (ii) there was good representation across five different industries; (iii) all roles were relevant to project management; (iv) AI exposure varied among participants, which helped to explore different perspectives on AI's impact across various levels of expertise and usage; and (v) participants came from different organizational levels to understand

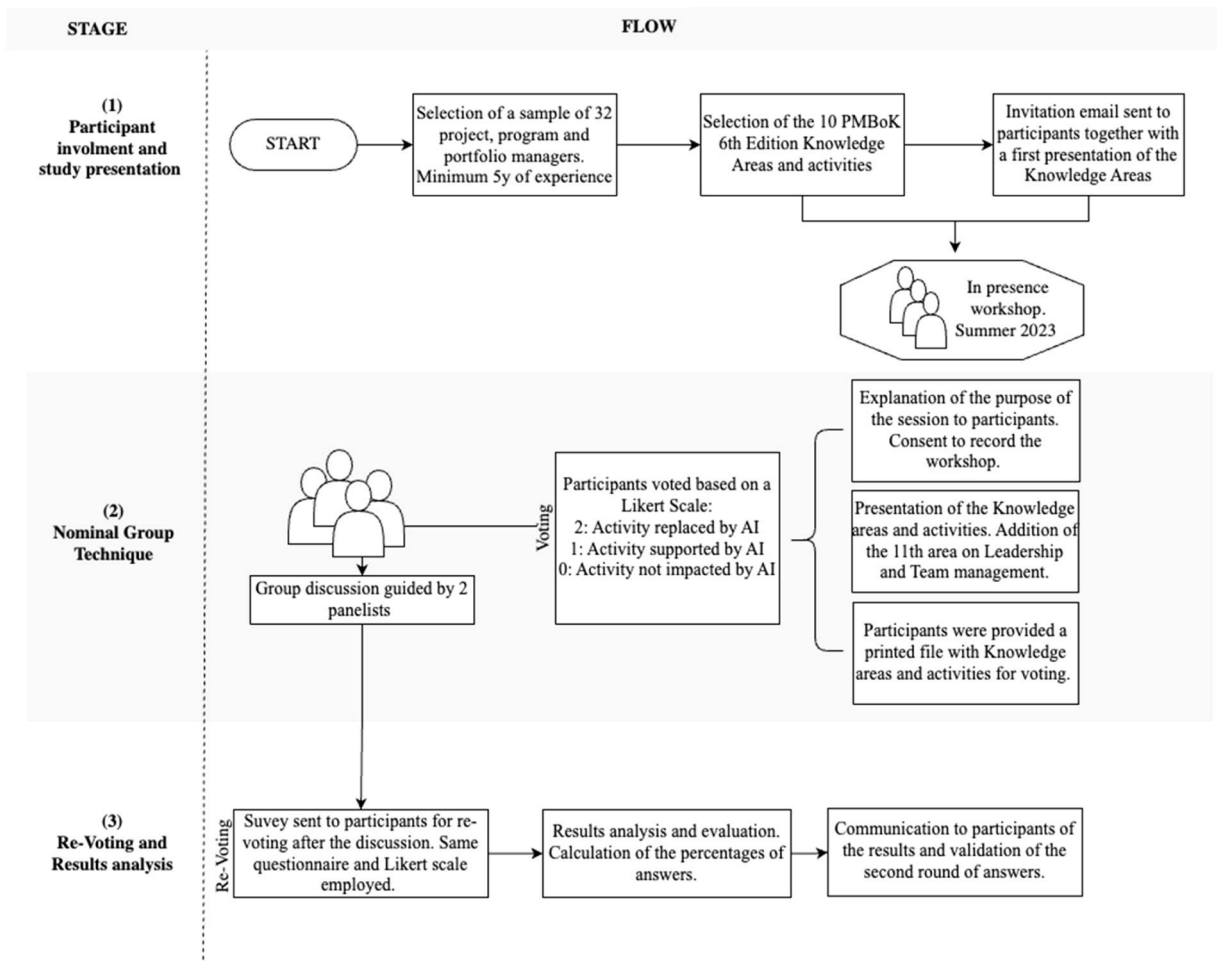


Fig. 1. Research steps and nominal group technique process.

how AI impacts decision-making at various levels within organizations.

### 3.4. Research steps

The steps followed for conducting the research were taken from (Mullen et al., 2021). The research was thus methodologically articulated around 3 steps, which are graphically represented in Fig. 1.

Step 1 involved the invitation of participants and definition of the Knowledge Areas. As highlighted in the previous paragraph, the methodological step of the idea generation was revised as participants were directly provided, in the invitation email, with an overview of project management activities to be evaluated during the workshop. However, no specific guidance was given regarding AI, giving professionals the opportunity to consider the technologies that could be used alongside their activities. This was done with the dual purpose of not constraining the initiative of project managers in terms of potential technologies to consider and allowing them to contemplate the possible extent of integration in their daily work activities. Activities included in Step 2 were performed during the workshop, which took place in summer 2023. The in-presence focus group commenced with a concise introduction, wherein the purpose of the session was explained to participants. Further information-sharing during the introductory phase involved providing participants with an information sheet and obtaining their consent for study participation and for recording the entire workshop. Subsequently, the knowledge areas were briefly introduced, along with the activities they encompassed. The possibility of incorporating an eleventh knowledge area related to "Leadership and Team Management" was discussed with the 32 participants, and the associated activities to be considered were defined. After the two presenters briefly explained the list of activities and knowledge areas, a printed sheet containing the same information was provided to the participants. After that, participants were tasked with assigning a ranking to each listed activity based on the following Likert scale: 2 for the complete replacement of AI for the activity, 1 for a transformation or support of the activity by AI, and 0 for no impact of these new technologies on the activity. After the completion of this task, overall assessment calculations were performed, and the results were presented and discussed with the workshop participants. Following the discussion, in Step 3, two days after the workshop, the same questionnaire was sent to participants for the re-voting phase following the collective discussion. The Likert scale used remained unchanged. The results section includes the presentation of the opinions expressed by participants both during the workshop and in the re-voting phase. However, the comments are focused on the opinions expressed definitively in the re-voting phase, which were obtained after the collective discussion as methodologically suggested by (Harvey and Holmes, 2012)

**Table 3**  
Voting and re-voting. Percentage of project professional votes per single activity.

Activities	Voting			Re-Voting		
	Replaces	Supports	No Impact	Replaces	Supports	No Impact
Developing and updating the project charter	9,4 %	87,5 %	3,1 %	12,5 %	81,3 %	6,3 %
Monitoring Project progress and making adjustments as necessary	21,9 %	78,1 %	0,0 %	21,9 %	78,1 %	0,0 %
Performing integrated change control	6,3 %	53,1 %	40,6 %	6,3 %	53,1 %	40,6 %
Defining Project scope	15,6 %	50,0 %	34,4 %	12,5 %	34,4 %	53,1 %
Creating the WBS	43,8 %	56,3 %	0,0 %	46,9 %	53,1 %	0,0 %
Monitoring Project scope	9,4 %	71,9 %	18,8 %	6,3 %	75,0 %	18,8 %
Defining and sequencing Project activities	59,4 %	40,6 %	0,0 %	53,1 %	46,9 %	0,0 %
Estimating activities resources and duration	68,8 %	31,3 %	0,0 %	71,9 %	28,1 %	0,0 %
Developing the Project schedule	75,0 %	25,0 %	0,0 %	71,9 %	28,1 %	0,0 %
Monitoring the Project schedule	50,0 %	50,0 %	0,0 %	53,1 %	46,9 %	0,0 %
Estimating Project costs	65,6 %	34,4 %	0,0 %	65,6 %	34,4 %	0,0 %
Monitoring Project costs and cash flows	84,4 %	15,6 %	0,0 %	84,4 %	15,6 %	0,0 %
Identifying Project quality requirements	34,4 %	53,1 %	12,5 %	31,3 %	56,3 %	12,5 %
Monitoring Project quality standards	43,8 %	53,1 %	3,1 %	40,6 %	53,1 %	6,3 %
Identifying necessary project resources	31,3 %	65,6 %	3,1 %	28,1 %	68,8 %	3,1 %
Monitoring Project resources availability and saturation	68,8 %	31,3 %	0,0 %	71,9 %	28,1 %	0,0 %
Communicating Project status and progress to stakeholders	31,3 %	40,6 %	28,1 %	21,9 %	50,0 %	28,1 %
Managing communications within Project team	9,4 %	71,9 %	18,8 %	9,4 %	59,4 %	31,3 %
Identifying Project risks	31,3 %	68,8 %	0,0 %	21,9 %	78,1 %	0,0 %
Prioritizing Project risks by assigning probability of occurrence	53,1 %	46,9 %	0,0 %	53,1 %	46,9 %	0,0 %
Performing Project Risk responses	3,1 %	87,5 %	9,4 %	3,1 %	81,3 %	15,6 %
Identifying Project Procurement needs	59,4 %	40,6 %	0,0 %	62,5 %	37,5 %	0,0 %
Selecting suppliers	18,8 %	78,1 %	3,1 %	18,8 %	78,1 %	3,1 %
Managing contracts with suppliers	37,5 %	43,8 %	18,8 %	25,0 %	50,0 %	25,0 %
Identifying and analyzing project stakeholders	12,5 %	84,4 %	3,1 %	12,5 %	81,3 %	6,3 %
Monitoring and engaging stakeholders	0,0 %	65,6 %	34,4 %	0,0 %	68,8 %	31,3 %
Assigning tasks and responsibilities to team members	18,8 %	68,8 %	12,5 %	12,5 %	75,0 %	12,5 %
Monitoring team members' performance and providing feedback	0,0 %	75,0 %	25,0 %	0,0 %	75,0 %	25,0 %
Coaching, leading and motivating the Project team	0,0 %	15,6 %	84,4 %	0,0 %	15,6 %	84,4 %
Making decisions and solving conflicts as they arise	0,0 %	18,8 %	81,3 %	0,0 %	15,6 %	84,4 %

#### 4. Results

In this section, we will discuss the conclusive results of the analysis pertaining to the re-voting phase conducted by the respondents. As previously mentioned, participants were asked to provide their responses using a Likert scale. A score of 2 was assigned by participants to activities for which a complete replacement by AI was supposed, signifying the interviewee's belief that AI was expected to entirely take over the activity. A score of 1 indicated a supportive role for AI, suggesting that AI would assist the Project Manager in executing the activity, thereby transforming the task from being entirely manual to being performed collaboratively by humans and machines. Lastly, a score of 0 denoted no impact of AI on the execution of the activity. The total of the scores assigned to each activity enabled the calculation of an overall score for each participant, serving as an indicator of their confidence in AI's capacity to replace a substantial portion of the tasks presently undertaken by Project Managers. The cumulative score for each respondent ranged from a minimum of 0, indicating the belief that none of the 30 activities could be influenced by AI, to a maximum of 60, reflecting a score of 2 assigned to each activity. Consequently, the higher the score attained by the respondent, the greater their confidence in the anticipated impact of AI on the role of the project manager. Among the 32 participants, the average overall score achieved was 34.46, with the highest score recorded at 45 and the lowest at 26. The calculated standard deviation stood at 5.31. These values indicate a moderate inclination towards considering the potential for a complete replacement by AI in PM activities. While the average score is noteworthy, it suggests that managers anticipate, at the very least, a partial substitution of AI for tasks traditionally performed by Project Managers. Upon delving into the results specific to various industry sectors, distinctive trends emerged. Project Managers operating in the "Pharma & Biotech" sector exhibited an average score of 33.83, ranging from a high of 45 to a low of 27, with a standard deviation of 5.81. Similarly, respondents from the "Consultancy" sector garnered an average score of 34.50, spanning from a high of 43 to a low of 27, with standard deviation of 5.82. Within the area of "Industrial Technologies, Infrastructure, and Automation," Project Managers secured the second-highest average confidence score at 34.33, with the highest and lowest scores recorded as 41 and 26, respectively, and a standard deviation of 5.34. Project Managers affiliated with the "Fintech & Banking" sector displayed the lowest average score of 33.44, ranging from a high of 44 to a low of 27, with a standard deviation of 5.23. Lastly, Project Managers in the "Automotive" sector

**Table 4**  
AI impact on the examined PM Knowledge Areas.

Activity	AI Impact	SD
Project Cost Management	1,75	0.090
Project Schedule Management	1,62	0.095
Project Resource Management	1,48	0.235
Project Quality Management	1,26	0.075
Project Procurement Management	1,26	0.267
Project Risk Management	1,20	0.265
Project Integration Management	0,97	0.236
Project Scope Management	0,97	0.366
Project Stakeholder Management	0,87	0.185
Project Communication Management	0,85	0.080
Leadership And Team Management	0,51	0.368

attained the highest average confidence score of 36.20, encompassing a high of 40 and a low of 33; this industry demonstrated the highest sectoral homogeneity, boasting a standard deviation of 3.19. Finally, the most relevant analysis concerns the assessment of individual activities, which is crucial for understanding the extent to which, according to the respondents, their profession consists of tasks that are at risk of being completely replaced by AI. Table 3 For each activity, Table 3 displays the percentage of PM professionals who believe AI could replace the activity, support the activity, or have no impact on it. The results are presented for the two rounds: the initial voting and re-voting.

The outcomes of this table yield valuable insights into activities that garnered the highest and lowest scores. Among activities attaining the highest scores (84.4 % of participants voting for replace), is "Monitoring Project Costs and Cash Flows," with a corresponding average score for complete replacement at 1.84. This implies a conviction that AI can effectively contribute to managing project finances, overseeing costs, and handling cash flow processes. Likewise, both "Estimating activities' resources and duration" and "Developing the Project Schedule" received scores of 1.72, with the 71.9 % of participants signaling the potential AI's capability to replace the resource allocation and project scheduling tasks completely. "Estimating Project Costs" (1.66) and "Identifying Project procurement needs" (1.63) were also identified as areas where AI is anticipated to potentially replace humans, offering advanced cost estimation capabilities, and aiding in procurement decision-making. Conversely certain activities were perceived as less susceptible to AI's impact, as indicated by their lower scores. Both "Coaching, leading, and motivating the Project Team" and "Making decisions and solving conflicts as they arise" received scores of 0.16, suggesting a belief that these tasks will still rely on human interaction and the skills of the Project Manager. "Defining Project Scope" (0.59) is another activity where human expertise was deemed essential, given the understanding required to effectively establish project boundaries. Similarly, "Performing Integrated Change Control" (0.66) and "Monitoring and engaging stakeholders" (0.69) were recognized as areas where the judgment and relationship management abilities of the Project Manager are expected to remain crucial. Considering the entire sample of 32 participants, the average index for these scores was 1.14, with a standard deviation of 0.44. This result suggests that project professionals start perceiving AI as a non-human component which is likely to support or transform the way they perform their tasks in the following years. To conclude, Table 4 outlines the average score (0 "not impacted – 2 = "replacement") and the standard deviation for knowledge areas that is derived calculating the average value of the scores assigned to each activity within the respective knowledge areas. In this case, 'Project Cost Management' shows the highest AI impact with a score of 1.75 and a low standard deviation of 0.090, indicating strong consensus among participants regarding the significant influence of AI in this area. In contrast, 'Leadership And Team Management' not only has the lowest impact score (0.51) but also the highest standard deviation (0.368), suggesting more variable opinions and less consensus on the effectiveness of AI in these more human-centric management activities.

## 5. Discussion

### 5.1. 5.1 The potential of AI for supporting project managers

This exploratory study offers insights into the potential trends of AI replacing human-based tasks in project management. The research is built on data gathered from 32 experts in project management. These experts, initially invited to participate in the workshop and to the subsequent survey, demonstrated enthusiasm in providing their inputs and insights on the topic. The use of the NGT method to gather information allowed for prioritizing the list of 30 predefined project management activities based on a prioritization from tasks entirely replaced by AI to tasks unaffected by AI. The findings of this study suggest that project managers perceive planning and cost control, scheduling, and resource management as activities with a more immediate prospect of being replaced by AI. This is also supported by existing literature, which predicts a greater impact of AI on these activities in the future (; Fridgeirsson et al., 2021; Holzmann, Zitter and Peshkess, 2022). This could suggest that the higher-skilled work activities that remain are cognitively challenging, underscoring the possibility that humans are indispensable in these roles. However, what these papers do not explore is how AI can function as a support, not merely replacing but transforming how certain activities are performed through human-machine interaction (Gil, Martínez Torres and González-Crespo, 2020). This opens up a different perspective. In fact, contrary to what has been observed in past studies, and in line with some job polarization studies, there exists a portion of the remaining non-automated activities that are high-skilled but have the potential to be transformed by AI (Goos, Manning and Salomons, 2009; Harrigan, Reshef and Toubal, 2021). For example, Project Stakeholder Management (75 %) and Project Integration Management (70.83 %), have been identified as project management domains likely to be supported by the use of AI. These areas are not typically highlighted in studies as those that could be impacted by AI (Davahli, 2020), however, our results demonstrate that they have a high potential to be "transformed" by new technologies.

What is interesting to note is that from the participants' perspective, is that the use of technologies for these "support" activities is not viewed as a threat for replacement. Rather, considering an Activity Theory perspective (Kaptelinin & Nardi, 2006; Allen, Karanasios and Slavova, 2011), it is seen as tools that mediate human activity through an interaction that transform the activity itself. For example, regarding project integration management a participant notes: 'AI's integration with systems like SAP, which enables the extraction of real-time insights, has the potential to radically alter our current methods. This integration could significantly enhance efficiency by optimizing data management and leveraging data-driven insights, thus reducing the dependency on manual human input significantly.' This comment indicates that AI is viewed as a means to fundamentally alter current coordination activities. By integrating AI with systems like SAP, it facilitates a shift towards more data-driven decision-making processes enabling human agents to base their decisions on robust data insights. Thus, the AI is not replacing human, but it is rather changing the nature of the activity that is transformed into a data informed decision making. On the same line, another participant state that for schedule risk management AI allows to produce "what if scenarios, allowing to design multiple Gantt charts with different critical paths and highlighting critical elements, but leaving the Project Manager

the responsibility of critically evaluating and validating the most suitable network diagram". Meaning that the interaction between humans and machine is generating an innovative and "data augmented" process for performing schedule risk management.

Also for the three knowledge areas that show a higher potential impact of AI, some participants have noted that these technologies are more often perceived as means to support activities rather than as threats for complete replacement. In this regard, a project manager working in infrastructure, emphasized the necessity of maintaining human oversight, particularly in complex project scenarios where sub-projects with allocated budgets coexist. He stated: *"In such cases, the failure of a single sub-project may elude AI's detection if it solely focuses on the overarching project, failing to consider internal sub-project failures. Therefore, while AI complements the monitoring process, human involvement remains indispensable to ensure a comprehensive oversight"*; Similarly, according to other respondents, AI's ability to tailor modifications to specific projects characteristics is limited *"Actually, I have already tested that AI lacks a reliable and long memory of previously implemented changes across projects and, consequently, it would only work as a supportive tool, augmenting Project Manager's capabilities in monitoring project progress and making adjustments"*. The perspective shared by the participant underscores the transformative role of AI as primarily augmentative, particularly in specific phases of an activity such as data collection regarding scenarios.

Among the areas perceived by project managers as having a lower risk of replacement, there is the definition and monitoring of the project scope. This contrasts with findings from other studies as (Davahli, 2020; Fridgeirsson et al., 2021; Holzmann, Zitter and Peshkess, 2022), in which this area was seen as one of the most impacted by AI. However, this result can be partially justified by a statement made by a participant during the workshop: *"It is important to make a distinction between projects with a high innovation content and more standardised ones. For the latter, AI could almost replace the PM in defining the scope, as the work packages would closely align with the company's historical project data. However, the complexity and uncertainty associated with defining the scope increase for projects with a high innovation rate. Consequently, the more complexity and innovation rate grow, the more AI becomes less capable of aiding the Project Manager"*.

It remains interesting in our view to note how areas such as communication and stakeholder management, traditionally considered to have a lower impact from AI according to the literature (Bodea, Mitea and Stanciu, 2020; Davahli, 2020), exhibit values close to 1 in this study. This aligns with the anticipation that these activities might undergo transformation by AI in the coming years. In these areas, indeed, potential supporting techniques emerged during the discussion, such as clustering and NLP for sentiment analysis among stakeholders. Some participants emphasized that for internal project team communication, future applications could involve chatbots and classification algorithms for immediate information retrieval during the project. However, a participant noted that *"Communicating project status and progress to stakeholders is an activity that requires a great human component. I think that a Project Manager knows the stakeholders better than any technology, and, as a result, communication can benefit only from a closer human relationship"*. To conclude, according to the managers, the only area that will not be replaced by AI in the near future is Leadership and Team Management. A participant's statement on this matter underscores this perspective: *"In these activities, the relational and emotional component is too important. No matter how advanced and intelligent AI may be in computation and processing results, a technology like AI will never be able to match the human intellect in the ability to inspire and guide people. Project Manager is not just an operational role, but one deeply connected to soft skills. That's why I don't believe AI will ever have any impact on such activities."* This underscore that the human element in these activities is too crucial for AI to be considered even in a supporting function.

## 5.2. Implication for theory and practice

From a theoretical standpoint, this paper contributes to the broader management literature concerning the perspective on the gradual replacement of new technologies for tasks currently carried out by humans (Arntz, Gregory and Zierahn, 2016; Frey and Osborne, 2017; Fossen and Sorgner, 2019). In particular, compared to the current literature on project management (Fridgeirsson et al., 2021; Holzmann, Zitter and Peshkess, 2022), our work further explores which activities might undergo transformation due to AI support. We conclude that, predominantly, project managers perceive AI as a means for augmenting their capabilities rather than as a threat to their roles. This finding aligns with the Activity Theory perspective, which emphasizes that tools and technologies serve as mediators in human activities, enhancing human capabilities rather than simply replacing them. By framing AI as a tool that transforms activities, we highlight its role in supporting and extending the skills of project managers, outlining the prospect of a collaborative integration of human and machine capabilities in project management. Cross-referencing the results of this study with the occupational map proposed by Fossen and Sorgner (2019), it appears that the overall findings align closely with those presented in our study. The authors categorize the occupations of "General and Operations Managers" within the domain of "Rising Stars" occupations. In this quadrant, occupations are profoundly influenced by transformative machine processes and AI advent, yet the substantial impact does not culminate in the replacement of human workers. As a result, there is a minimal risk of destructive replacement. However, these occupations are undergoing substantial changes in work processes due to the advent of digitalization and AI. This classification coincides with the results obtained in our study, where managers expressed a perspective of transformation rather than replacement by AI for a greater number of activities. Therefore, categorizing the project manager profession within the "Rising Star" domain, encompassing roles that require elevated levels of creative and social intelligence, implies that project managers are not likely to face replacement in the immediate future. Instead, they are anticipated to collaborate with emerging AI technologies in activities that undergo transformation. Nevertheless, this transformation will entail significant changes in their professions, potentially necessitating the acquisition of additional qualifications to remain competitive, even though the risk of entire replacement by machines remains relatively low (Felten, Raj and Seamans, 2018). Hence, from an operational standpoint, there is a clear need for upskilling among project managers, which might include acquiring proficiency in machine learning software, mastering data analytics for informed decision-making, and developing a strong understanding of emerging technologies (Verma, Lamsal and Verma, 2022). If project

managers do not align their skills with the emerging technological landscape, there could be a heightened risk of skill-biased technological change (Fernandez, 2001) which might lead to an increase in an inequality in wages for project managers who possess a lower skillset. The implications for practice are profound in light of the theoretical insights provided in this study. As project managers face the evolving landscape shaped by the gradual replacement of traditional tasks by new technologies, the imperative for proactive adaptation becomes evident. To effectively engage with transformative digitalization and AI advancements, companies should prioritize project managers upskilling initiatives. Howard, (2019) mentions human-machine interaction and the use of sensors as support as one of the primary technologies that operators should learn to utilize. However, observing the trends reported in PM literature, which include AI applications in project portfolio selection (Costantino, Di Gravio and Nonino, 2015; Nazemi, Abbasi and Omid, 2015) or stakeholder classification (Pérez Vera and Bermudez Peña, 2022; Mariani, Navrotska and Mancini, 2023), it becomes evident that the required upskilling involves not only the mechanical implementation of models for automatizing repetitive tasks but also their utilization for strategic purposes. This encompasses supporting scenario analysis, strategic prediction, and decision-making in a more comprehensive sense (Borges et al., 2021). In synthesis, as the profession embraces these advancements, the conclusion drawn is that the future-ready project manager must not only master the technical deployment of AI but also cultivate a strategic acumen for optimal utilization of these transformative technologies.

## 6. Limitations and conclusion

This study provides an initial perspective, obtained through a Nominal Group Technique (NGT) session, regarding the potential replacement of some tasks performed by the project manager with AI. Although the results lean towards a continued strong human component, which will not lead to a "collapse" of the project manager profession in the coming years, they suggest a transformed impact of AI on many of the examined activities. This has led us to highlight certain theoretical implications, such as categorizing the project manager discipline as a "Rising Star" profession (Fossen and Sorgner, 2019), and practical implications, like the need for upskilling to navigate this changing landscape. However, this study is not without limitations. The method employed, the NGT group, as mentioned earlier, has certain drawbacks, such as the potential for excessive group perspectives to influence individual judgments, the absence of selecting a statistically significant sample and the dependence on a specific format with predetermined steps which may unintentionally limit the exploration of certain facets, possibly overlooking valuable insights (Langford, Schoenfeld and Izzo, 2002). Aspects related to group dynamics may have been mitigated through the re-voting via survey, but they still persist as limitations of the method and, consequently, of the study itself. A potential avenue for future research could involve studying the same topic with a rigorously statistical approach, such as a survey. Another potential avenue for future research could involve engaging IT project managers. The current study has indeed investigated the perspectives of experienced project managers, while it has not examined the viewpoint of IT industry experts, as done in previous studies (Gil, Martínez Torres and González-Crespo, 2020). IT project managers, with their specialized focus on technology-driven projects, may have distinct insights into the integration of AI within their specific domain. Their considerations might encompass the technical aspects, such as the compatibility of AI systems with existing IT infrastructure, cybersecurity concerns, and the potential for AI to enhance or disrupt established technological processes. Finally, this study focused exclusively on the perceived impact of analytical AI systems in project management, particularly those applied to forecasting, monitoring, and optimization tasks. We did not explore project managers' perceptions of generative AI tools—such as ChatGPT—which are increasingly used for communication, documentation, and support activities. Future research could investigate how these tools are perceived in terms of their potential to transform or augment project management practices, especially in areas involving knowledge sharing and soft skills. This study focused exclusively on the perceived impact of analytical AI systems in project management, particularly those applied to forecasting, monitoring, and optimization tasks. We did not explore project managers' perceptions of generative AI tools—such as ChatGPT—which are increasingly used for communication, documentation, and support activities. Future research could investigate how these tools are perceived in terms of their potential to transform or augment project management practices, especially in areas involving knowledge sharing and soft skills.

Finally, another possible avenue for future research is the need to systematically map the new competencies required by project managers for the necessary upskilling to work in a world where the integration between AI and the workspace is increasingly advancing. This avenue for future research could entail a comprehensive exploration of the skills and knowledge areas that project managers need to cultivate for effective collaboration with AI technologies, identifying not only technical proficiencies but also the softer skills and adaptive capabilities crucial for fostering synergy between human project managers and AI systems.

## 7. Implication for policy-making

The findings of this study offer relevant insights for policy-makers aiming to support workforce transitions in project-based environments. Rather than focusing solely on job replacement, policies should address the transformation of existing roles through AI augmentation – as already outlined in literature and practice (Fossen and Sorgner, 2019; World Economic Forum, 2025). This includes promoting continuous upskilling programs for project managers, encouraging the integration of AI literacy into professional standards, and supporting human-centric AI design in managerial contexts (Ng et al., 2021). Given the heterogeneous impact across tasks outlined in this paper, tailored policy measures are needed to ensure equitable and effective adoption of AI in project work. Finally, our findings highlight that project managers perceive AI primarily as a supportive tool rather than a replacement, especially in tasks involving leadership, stakeholder engagement, and complex decision-making. This suggests that regulatory and governance frameworks should support innovation but also ensure that AI adoption in project management preserves human oversight and decision transparency, particularly in areas where human judgment remains essential.

## CRediT authorship contribution statement

**Mauro Mancini:** Writing – review & editing. **Costanza Mariani:** Writing – original draft, Methodology, Investigation, Data curation, Conceptualization.

## Data availability

Data will be made available on request.

## References

- Acemoglu, D., Restrepo, P., 2020. Robots and jobs: evidence from us labor markets (Available at:). *J. Political Econ.* 128 (6), 2188–2244. <https://doi.org/10.1086/705716>.
- Acharya, D.B., Kuppan, K., Divya, B., 2025. Agentic AI: Autonomous intelligence for complex goals—a comprehensive survey. *IEEE Access* 13, 18912–18936. <https://doi.org/10.1109/ACCESS.2025.3532853>.
- Allen, D., Karanasios, S., Slavova, M., 2011. Working with activity theory: context, technology, and information behavior. *J. Am. Soc. Inf. Sci. Technol.* 62 (4), 776–788. <https://doi.org/10.1002/asi.21441>.
- Allen, J., Dyas, J., Jones, M., 2004. Building consensus in health care: a guide to using the nominal group technique. *Br. J. Community Nurs.* 9 (3), 110–114. <https://doi.org/10.12968/bjcn.2004.9.3.12432>.
- Arntz, M., Gregory, T., Zierahn, U., 2016. A comparative analysis. *Risk Autom. Jobs OECD Ctries.*
- Auth, G., Jokisch, O., Dürk, C., 2019. Revisiting automated project management in the digital age – a survey of AI approaches. *Online J. Appl. Knowl. Manag.* 7 (1), 27–39. [https://doi.org/10.36965/ojakm.2019.7\(1\)27-39](https://doi.org/10.36965/ojakm.2019.7(1)27-39).
- Autor, D.H., Dorn, D., 2013. The growth of low-skill service jobs and the polarization of the us labor market. *Am. Econ. Rev.* 103 (5), 1553–1597.
- Azharuddin, M. et al. (2022) 'Smart Project Management System (SPMS) - An Integrated and Predictive Solution for Proactively Managing Oil & Gas client Projects', in *ADIPEC*, Abu Dhabi, UAE, October 2022, pp. 20–50.
- Bahroun, Z., et al., 2023. Artificial intelligence adoption in project scheduling: a systematic review, bibliometric analysis, and prospects for future research. *Manag. Syst. Prod. Eng.* 31 (2), 144–161. <https://doi.org/10.2478/mspe-2023-0017>.
- Balali, A., et al., 2020. Improving the results of the Earned Value management technique using artificial neural networks in construction projects. *Symmetry* 12 (10), 1–17. <https://doi.org/10.3390/sym12101745>.
- Bessen, J., 2016. How computer automation affects occupations. *Technol. jobs skills.*
- Bodea, C., et al., 2020. *Artif. Intell. Impact Proj. Manag.* ' (Oct. 50).
- Bodea, C., Mitea, C., Stanciu, O., 2020. Artificial intelligence adoption in project management: main drivers, barriers and estimated impact'. *Proc. 3rd Int. Conf. Econ. Soc. Sci.* 758–767. <https://doi.org/10.2478/9788366675162-075>.
- Borges, A.F.S., et al., 2021. The strategic use of artificial intelligence in the digital era: systematic literature review and future research directions. *Int. J. Inf. Manag.* 57, 102225. <https://doi.org/10.1016/j.ijinfomgt.2020.102225>.
- Brynjolfsson, E., McAfee, A., 2014. *The second machine age*, First Ed. W. W. Norton & Company, New York.
- Campi, M., Dueñas, M., 2019. Intellectual property rights, trade agreements, and international trade. *Res. Policy* 48 (3), 531–545. <https://doi.org/10.1016/j.respol.2018.09.011>.
- Chiarini, A., et al., 2024. Do automation and AI impact on job reduction? A study on perceived risk of losing job among white-collar in the Italian manufacturing companies. *Prod. Plan. Control* 35 (16), 2198–2211. <https://doi.org/10.1080/09537287.2023.2244925>.
- Chui, M., Manyika, J., Miremadi, M., 2016. where Mach. could Replace Hum. where they Can. 't (yet) Tech. Potential Autom. differs Dram. Across Sect. Act.
- Cicmil, S., 2006. Understanding project management practice through interpretative and critical research perspectives. *Proj. Manag. J.* 37 (2), 27–37. <https://doi.org/10.1177/875697280603700204>.
- Clifton, J., Glasmeier, A., Gray, M., 2020. When machines think for us: the consequences for work and place. *Camb. J. Reg. Econ. Soc.* 13 (March), 3–23. <https://doi.org/10.1093/cjres/rsaa004>.
- Costantino, F., Di Gravio, G., Nonino, F., 2015. Project selection in project portfolio management: an artificial neural network model based on critical success factors. *Int. J. Proj. Manag.* 33 (8), 1744–1754. <https://doi.org/10.1016/j.ijproman.2015.07.003>.
- Davahli, M.R., 2020. Last State Artif. Intell. Proj. Manag. ' Comput. Sci. [Prepr.
- Degrype, C., 2016. Digit. Econ. Impact Labour Mark.
- Denning, K.H., Jones, L., Sampson, E.L., 2013. Preferences for end-of-life care: a nominal group study of people with dementia and their family carers. *Palliat. Med.* 27 (5), 409–417. <https://doi.org/10.1177/0269216312464094>.
- Dong, H., et al., 2025. NNG-mix: improving semi-supervised anomaly detection with pseudo-anomaly generation. *IEEE Trans. Neural Netw. Learn. Syst.* 36 (6), 10635–10647. <https://doi.org/10.1109/TNNLS.2024.3497801>.
- European Commission, 2016. On the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC. General Data Protection Regulation) (Text with EEA relevance.
- European Commission, 2020. A new Industrial Strategy for a globally competitive, green and digital Europe'. *European File*, pp. 2–3 (March).
- European Commission, 2024. Regulation (EU) 2024/1689 of the European Parliament. and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence. Available at: (<http://data.europa.eu/eli/reg/2024/1689/oj>).
- Felten, B.E.W., Raj, M., Seamans, R., 2018. A method to link advances in artificial intelligence to occupational abilities. *AEA Pap. Proc.* 108 (May), 54–57.
- Fernandez, R.M., 2001. Skill-biased technological change and wage inequality: evidence from a plant retooling. *am. j. sociol.* 107 (2), 273–320. 10.1086/324009.
- Fuerrriegel, S., et al., 2024. Generative AI. *Bus. Inf. Syst. Eng.* 66 (1), 111–126. <https://doi.org/10.1007/s12599-023-00834-7>.
- Flyvbjerg, B., et al., 2022. AI action how hong kong development bureau built pss earlywarningsign system public works projects' SSRN 1–28.
- Fossen, F., Sorgner, A., 2019. Mapping the future of occupations: transformative and destructive effects of new digital technologies on jobs article'. *Foresight STI Gov.* 13 (2), 10–18. <https://doi.org/10.17323/2500-2597.2019.2.10.18.10>.
- Frey, C.B., Osborne, M.A., 2017. The future of employment: how susceptible are jobs to computerisation? *Technol. Forecast. Soc. Change* 114, 254–280. <https://doi.org/10.1016/j.techfore.2016.08.019>.
- Fridgeirsson, T.V., 2016. Reference class forecasting in Icelandic transport infrastructure projects. *Transp. Probl.* 11 (2), 103–115. <https://doi.org/10.20858/tp.2016.11.2.10>.
- Fridgeirsson, T.V., et al., 2021. An authoritative study on the near future effect of artificial intelligence on project management knowledge areas. *Sustainability* 13 (4), 1–20. <https://doi.org/10.3390/su13042345>.
- Gallagher, M., et al., 1993. The nominal group technique: a research Tool for general practice? *Fam. Pract.* 10 (1), 76–81. <https://doi.org/10.1093/famp/10.1.76>.
- Gil, J., Martínez Torres, J., González-Crespo, R., 2020. The application of artificial intelligence in project management research: a review. *Int. J. Interact. Multimed. Artif. Intell.* <https://doi.org/10.9781/ijimai.2020.12.003>. In Press.
- Goos, M., Manning, A., Salomons, A., 2009. Job polarization in Europe. *Am. Econ. Rev.* 58–63. <https://doi.org/10.1257/aer.99.2.58>.
- Haenlein, M., Kaplan, A., 2019. A brief history of artificial intelligence: on the past, present, and future of artificial intelligence. *Calif. Manag. Rev.* 61 (4), 5–14. <https://doi.org/10.1177/0008125619864925>.

- Harrigan, J., Reshef, A., Toubal, F., 2021. The march of the techies: job polarization within and between firms. *Res. Policy* 50 (7), 104008. <https://doi.org/10.1016/j.respol.2020.104008>.
- Harvey, N., Holmes, C.A., 2012. Nominal group technique: an effective method for obtaining group consensus. *Int. J. Nurs. Pract.* 18 (2), 188–194. <https://doi.org/10.1111/j.1440-172X.2012.02017.x>.
- Hilgsmann, M., 2013. Nominal group technique to select attributes for discrete choice experiments: an example for drug treatment choice in osteoporosis Patient Prefer. Adherence 7213313910.2147/PPA.S38408.
- Holzmann, V., Zitter, D., Peshkess, S., 2022. The expectations of project managers from artificial intelligence: a delphi study, 53 (5), 438–455. <https://doi.org/10.1177/87569728211061779>.
- Howard, J., 2019. Artificial intelligence: implications for the future of work. *Am. J. Ind. Med.* 62 (11), 917–926. <https://doi.org/10.1002/ajim.23037>.
- Hunt, W., Sarkar, S., Warhurst, C., 2022. Measuring the impact of AI on jobs at the organization level: lessons from a survey of UK business leaders. *Res. Policy* 51 (2), 104425. <https://doi.org/10.1016/j.respol.2021.104425>.
- Inan, T., Narbaev, T., Hazir, Ö., 2022. A machine learning study to enhance project cost forecasting. *IFAC Pap. Elsevier B. V.* 3286–3291. <https://doi.org/10.1016/j.ifacol.2022.10.127>.
- Jensen, A., Thuesen, C., Geraldi, J., 2016. 'The projectification of everything: projects as a human condition' *Proj. Manag. J. Proj. Manag.* J.4732134(Available at) ([www.pmi.org/PMJ](http://www.pmi.org/PMJ)).
- Kamooona, K., Budayan, C., 2019. Implementation of genetic algorithm integrated with the deep neural network for estimating at completion simulation. *Adv. Civ. Eng.* 2019, 1–15. ID 7081073.
- Kaptelinin, Nardi, 2006. *Act. Technol. Act. Theory Interact. Des.*
- Kassaymeh, S., et al., 2024. Software effort estimation modeling and fully connected artificial neural network optimization using soft computing techniques. *Clust. Comput.* 27 (1), 737–760. <https://doi.org/10.1007/s10586-023-03979-y>.
- Khatib, M.E., Zitar, R.A., Al-Nakeeb, A., 2021. 'The effect of AI on project and risk management in health care industry projects in the United Arab Emirates (UAE)'. *Int. J. Appl. Eng. Res.* 6, 1.
- Kiani, A., 2024. Artificial intelligence in entrepreneurial project management: a review, framework and research agenda. *Int. J. Manag. Proj. Bus.* <https://doi.org/10.1108/IJMPB-03-2024-0068>.
- Kinkel, S., Baumgartner, M., Cherubini, E., 2022. Prerequisites for the adoption of AI technologies in manufacturing – Evidence from a worldwide sample of manufacturing companies. *Technovation* 110, 102375. <https://doi.org/10.1016/j.technovation.2021.102375>.
- Langford, B.E., Schoenfeld, G., Izzo, G., 2002. Nominal grouping sessions vs focus groups. *Qual. Mark. Res. Int. J.* 58–70. <https://doi.org/10.1108/13522750210414517>.
- Leocádio, D., et al., 2024. Customer Service with AI-Powered Human-Robot Collaboration (HRC): a literature review. *Procedia Comput. Sci.* 232, 1222–1232. <https://doi.org/10.1016/j.procs.2024.01.120>.
- Long, D., Magerko, B., 2020. What is AI Literacy? Competencies and Design Considerations. in *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. ACM, New York, NY, USA, pp. 1–16. <https://doi.org/10.1145/3313831.3376727>.
- Mancini, M., Mariani, C., Manfredi, M., 2023. Nuclear decommissioning risk management adopting a comprehensive artificial intelligence framework: an applied case in an Italian site. *Prog. Nucl. Energy* 158, 104589. <https://doi.org/10.1016/j.pnucene.2023.104589>.
- Mariani, C., et al., 2025. The C-BA method: enhancing megaproject forecasting through the "Fifth Hand" principle. *Int. J. Manag. Proj. Bus.* 18 (8), 50–78. <https://doi.org/10.1108/IJMPB-11-2024-0281>.
- Mariani, C., Mancini, M., 2023. Selection of projects' primary and secondary mitigation actions through optimization methods in nuclear decommissioning projects. *Nucl. Eng. Des.* 407. <https://doi.org/10.1016/j.nucengdes.2023.112284>.
- Mariani, C., Navrotska, Y., Mancini, M., 2023. Project Stakeholder Classification: Application of unsupervised machine learning, benefits and limitations'. *Proj. Leadersh. Soc.* 2023, 100093. <https://doi.org/10.1016/j.plas.2023.100093>.
- McMillan, S.S., et al., 2014. Using the Nominal Group Technique: how to analyse across multiple groups. *Health Serv. Outcomes Res. Methodol.* 14 (3), 92–108. <https://doi.org/10.1007/s10742-014-0121-1>.
- McMillan, S.S., King, M., Tully, M.P., 2016. How to use the nominal group and Delphi techniques. *International Journal of Clinical Pharmacy*. Springer Netherlands, pp. 655–662. <https://doi.org/10.1007/s11096-016-0257-x>.
- Mullen, R., et al., 2021. A practical guide to the systematic application of nominal group technique. *Nurse Res.* 29 (1), 14–20. <https://doi.org/10.7748/nr.2021.e1777>.
- Müller, R., et al., 2024. Artificial intelligence and project management: empirical overview, state of the art, and guidelines for future research. *Proj. Manag. J.* 55 (1), 9–15. <https://doi.org/10.1177/87569728231225198>.
- Musbahi, O., et al., 2021. Public patient views of artificial intelligence in healthcare: A nominal group technique study. *Digit. Health* 7. <https://doi.org/10.1177/20552076211063682>.
- Naudé, A., Bormann, J., 2021. Using nominal group technique to identify key ethical concerns regarding hearing aids with machine learning. *Perspect. ASHA Spec. Interest Groups* 6 (6), 1800–1808. [https://doi.org/10.1044/2021\\_PERSP-21-00126](https://doi.org/10.1044/2021_PERSP-21-00126).
- Nazemi, A., Abbasi, B., Omid, F., 2015. Solving portfolio selection models with uncertain returns using an artificial neural network scheme. *Appl. Intell.* 42 (4), 609–621. <https://doi.org/10.1007/s10489-014-0616-z>.
- Nemlioglu, I., 2019. A comparative analysis of intellectual property rights: a case of developed versus developing countries. *Procedia Comput. Sci.* 158, 988–998. <https://doi.org/10.1016/j.procs.2019.09.140>.
- Nenni, M.E., et al., 2025. How artificial intelligence will transform project management in the age of digitization: a systematic literature review. *Manag. Rev. Q.* 75 (2), 1669–1716. <https://doi.org/10.1007/s11301-024-00418-z>.
- Ng, D.T.K., et al., 2021. Conceptualizing AI literacy: an exploratory review. *Comput. Educ. Artif. Intell.* 2. <https://doi.org/10.1016/j.caeai.2021.100041>.
- Nilsson, M., 2023. Early Trends 'AI PM' Surv. (<https://www.projectmanagement.com/articles/889823/early-trends-revealed-in-intermediate-results-from-ai-pm-survey>).
- Pajarinen, M., Rouvinen, P., Ekeland, A., 2015. *Comput. Threat. OneThird Finn. Nor. Employ.*
- Pan, Y., Zhang, L., 2021. Roles of artificial intelligence in construction engineering and management: A critical review and future trends. *Autom. Constr.* 122, 103517. <https://doi.org/10.1016/j.autcon.2020.103517>.
- Pérez Vera, Y., Bermudez Peña, A., 2022. A neuro-fuzzy inference system for stakeholder classification Sistema de inferencia neuro-difuso para la clasificación de las partes interesadas'. *Ingeniare. Rev. Chil. De Ing. ía* 30, 378–387.
- PMI (2017) *A Guide to the Project Management Body of Knowledge (PMBOK® Guide)*—Sixth Edition. Project Management Institute.
- Poba-Nzaou, P., et al., 2021. The impacts of artificial intelligence (AI) on jobs: an industry perspective. *Strateg. HR Rev.* 20 (2), 60–65. <https://doi.org/10.1108/shr-01-2021-0003>.
- Prasad, K.R., et al., 2024. AI in public-private partnership for IT infrastructure development. *J. High. Technol. Manag. Res.* 35 (1), 100496. <https://doi.org/10.1016/j.hitech.2024.100496>.
- Rankovic, N., et al., 2024. AI in Project Resource Management. In: *Recent Advances in Artificial Intelligence in Cost Estimation in Project Management*. Springer, pp. 231–268. [https://doi.org/10.1007/978-3-031-76572-8\\_6](https://doi.org/10.1007/978-3-031-76572-8_6).
- Rawashdeh, A., 2025. The consequences of artificial intelligence: an investigation into the impact of AI on job displacement in accounting. *J. Sci. Technol. Policy Manag.* 16 (3), 506–535. <https://doi.org/10.1108/JSTPM-02-2023-0030>.
- Ruiz, J.G., Torres, J.M., Crespo, R.G., 2020. The application of artificial intelligence in project management research: a review. *Int. J. Interact. Multimed. Artif. Intell.* 6 (6), 54–66. <https://doi.org/10.9781/ijimai.2020.12.003>.
- Sánchez-Fernández, Á., Díez-González, J. and Perez, H. (2025) 'Artificial Intelligence in Portfolio Selection Problem: A Review and Future Perspectives', in, pp. 252–264. Available at: [https://doi.org/10.1007/978-3-031-74186-9\\_21](https://doi.org/10.1007/978-3-031-74186-9_21).

- Schoper, Y., Ingason, H.T., 2019. Projectification and the impact on societies. *International Journal of Managing Projects in Business*. Emerald Group Holdings Ltd., pp. 517–521. <https://doi.org/10.1108/IJMPB-09-2019-288>
- Stebbins, R.A., 2001. Exploratory research in the social sciences. In: *Sage University Papers Series on Qualitative Research Methods*, 48. Sage, Thousand Oaks, CA: Sage. Thousand Oaks, CA.
- Susskind, R., Susskind, D., 2015. *The Future of the Professions*. Oxford University Press. <https://doi.org/10.1093/oso/9780198713395.001.0001>.
- Tariq, M.U., Poulin, M., Abonamah, A.A., 2021. Achieving operational excellence through artificial intelligence: driving forces and barriers. *Front. Psychol.* 12 (July). <https://doi.org/10.3389/fpsyg.2021.686624>.
- Turing, A., 1950. Computing machinery and intelligence. *Mind* Q. Rev. Psychol. Philos. 59 (236), 23–65. [https://doi.org/10.1007/978-3-319-53280-6\\_11](https://doi.org/10.1007/978-3-319-53280-6_11).
- Unesco, 2023. *AI4IA | Artificial Intelligence for Information Accessibility 2023*.
- Verma, A., Lamsal, K., Verma, P., 2022. An investigation of skill requirements in artificial intelligence and machine learning job advertisements. *Ind. High. Educ.* 36 (1), 63–73. <https://doi.org/10.1177/0950422221990990>.
- Waldman-brown, A., 2020. Redeployment or robocalypse? Workers and automation in Ohio manufacturing SMEs'. *Camb. J. Reg. Econ. Soc.* 13, 99–115. <https://doi.org/10.1093/cjres/rsz027>.
- Wang, C., et al., 2023. Future of jobs in China under the impact of artificial intelligence. *Financ. Res. Lett.* 55, 103798. <https://doi.org/10.1016/j.frl.2023.103798>.
- Wang, Y. and Jin, X. (2019) 'Structural risk of diversified project financing of city investment company in China based on the best worst method', (51608363). Available at: <https://doi.org/10.1108/ECAM-05-2019-0249>.
- Waters, C.K., 2007. *Nat. Context Explor. Exp. Introd. Three Case Stud. Explor. Res. Philos. Life Sci.* Available at: (<https://www.jstor.org/stable/23334262?seq=1&cid=pdf>).
- Wojan, T.R., 2019. Geographical differences in intellectual property strategies and outcomes: establishment-level analysis across the American settlement hierarchy. *Reg. Stud. Reg. Sci.* 6 (1), 574–595. <https://doi.org/10.1080/21681376.2019.1682651>.
- World Economic Forum, 2025. *Future of Jobs Report 2025: 78 Million New Job Opportunities by 2030 but Urgent Upskilling Needed to Prepare Workforces*.
- Zhang, C., Lu, Y., 2021. Study on artificial intelligence: the state of the art and future prospects. *J. Ind. Inf. Integr.* 23 (April), 100224. <https://doi.org/10.1016/j.jii.2021.100224>.