Theoretical Foundations of Artificial Intelligence-enabled Project Management: A Systematic Literature Review

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***Abstract*—Artificial intelligence (AI) is increasingly transforming project management (PM) practices, yet the theoretical foundations of AI-enabled project management remain fragmented and insufficiently synthesised. Without clearer theoretical grounding, research in this area risks remaining largely descriptive and application-oriented.**

This study aims to identify, map, and explain the theoretical perspectives used in research on AI-enabled project management. A systematic literature review (SLR) was conducted in accordance with PRISMA 2020 guidelines. The search covered Web of Science and Scopus and identified 712 database records published between 2015 and 2025. After screening and full-text eligibility assessment, 10 theory-oriented studies were retained as the core dataset.

The analysis shows that AI-enabled project management does not rely on a single dominant theory. Instead, the reviewed studies draw on several theoretical perspectives, including decision and behavioural theories, task–technology alignment, dynamic capabilities, stakeholder theory, complexity theory, information economics, and fuzzy set theory. Across the reviewed studies, AI is most often conceptualised as decision support or as an augmentation of managerial capabilities. The reviewed studies also differ in how AI is specified, ranging from relatively specific technologies and functions, such as generative AI, fuzzy AI models, predictive analytics, and AI-enabled monitoring, to broader conceptualisations such as AI assimilation and sociotechnical AI systems.

The study contributes by showing how theoretical lenses, specific theories, AI roles, explanatory mechanisms, and levels of analysis can be linked into explanatory chains. These chains are then aggregated into recurring explanatory configurations and emerging theoretical streams. AI technology / function types are used as an additional coding dimension to interpret technology-specific implications for project management. Given the small final sample of theory-oriented studies, the identified streams should be interpreted as emerging patterns within this body of literature rather than as definitive or generalisable classifications of the entire AI-enabled project management field.

***Keywords*—artificial intelligence, project management, AI-enabled project management, theoretical foundations, systematic literature review, phenomena-driven research, AI adoption**

I. INTRODUCTION

Interest in artificial intelligence (AI) has grown rapidly across disciplines, positioning it as a transformative force reshaping organisational processes, decision-making, and modes of coordination [1], [2]. In contemporary project management (PM), the increasing diffusion of AI is transforming both operational processes and managerial practices, reshaping how projects are planned, executed, and governed [3], [4]. This relevance is reflected in the rapid expansion of scholarly interest in AI-enabled project management [5], [6]. However, while empirical and application-oriented studies have proliferated, the theoretical foundations of this domain remain underdeveloped and fragmented [3], [7].

Despite the growing body of literature [6], [8], [9], there is a lack of systematic and theory-oriented syntheses that would clarify how AI-enabled project management is theorised. Existing reviews do not sufficiently explain how different theoretical lenses, conceptualisations of AI, and explanatory mechanisms combine to form coherent patterns of understanding. Consequently, the field lacks an integrative perspective that would move towards identifying underlying explanatory configurations and their implications [3], [10].

To address this gap, this study adopts a systematic literature review approach, designed and conducted in line with PRISMA 2020 guidelines [11], with a specific focus on theory. The review identifies, maps, and synthesises the theoretical foundations of AI-enabled project management research. Beyond cataloguing theories, the study develops a structured analytical framework capturing four interrelated layers: theory identification, theory positioning, conceptualisations of AI, and explanatory mechanisms linking AI and project management. In this study, explanatory chains refer to ordered links between theoretical lenses, specific theories, AI roles, explanatory mechanisms, and levels of analysis. Recurring combinations of these elements are treated as explanatory configurations, which are subsequently grouped into emerging theoretical streams. Building on this multi-layered analysis, the study identifies recurring explanatory chains that connect these elements across different studies.

The aim of the paper is therefore to answer the following research question: *How is AI-enabled project management theorised in the literature, and what recurring explanatory configurations and emerging theoretical streams can be identified from this body of research?* By addressing this question, the study moves beyond descriptive synthesis towards a more structured understanding of theorisation in this domain.

The study makes several contributions to the literature. First, it provides a systematic mapping of the theoretical foundations of AI-enabled project management, identifying the range of theories used and their disciplinary origins. Second, it clarifies how AI is conceptualised within project management research and how these conceptualisations relate to different explanatory mechanisms. Third, and most importantly, it identifies recurring explanatory configurations

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linking theoretical lenses, AI roles, mechanisms, and levels of analysis. In addition, it differentiates AI technology / function types to clarify technology-specific implications for project management. Fourth, it explains how these configurations form emerging theoretical streams making the analytical pathway from individual studies to broader patterns of theorisation more transparent. By doing so, the paper provides a foundation for future theory development in AI-enabled project management.

The remainder of the paper is structured as follows. The next section outlines the research methodology, including the coding and synthesis procedure used to develop explanatory chains and emerging theoretical streams. This is followed by the presentation of results, including the mapping of theoretical foundations and the identification of explanatory configurations and streams. The final section discusses the implications for theory and future research.

II. Literature Review

Project management has evolved over time from an early focus on planning, scheduling, and control to broader organisational, behavioural, and governance-oriented perspectives [7], [10]. This development suggests that project management should not be understood solely as a technical or operational activity, but as a complex field embedded in organisational, relational, and decision-making contexts [7], [10], [12], [13]. Early scholarship already argued that project management required stronger theoretical development and should be examined through multiple conceptual lenses rather than reduced to a set of instrumental techniques [12]. This view was later reinforced by the "project actuality" perspective, which emphasised that project work is socially embedded, context-dependent, and shaped by real actions and interactions rather than by formal models alone [13]. More recent research further highlights the diversity and maturity of project management scholarship, showing that the field has developed across multiple levels of analysis and types of inquiry [7], [10]. Overall, this body of literature indicates that project management is a theoretically diverse field in which different perspectives are needed to capture the complexity of projects and project organising.

In parallel, digital transformation has become an increasingly important context shaping contemporary project environments. Digital technologies influence how organisations operate, how information is processed and shared, and how decisions are made [1], [2], [14], [15]. In project settings, this is reflected in changing management practices, the growing use of data-driven tools, and increasing expectations regarding analytical support, automation, and responsiveness. Reviews of digital transformation describe it not only as a technological shift, but also as a broader organisational and strategic process that affects value creation, governance, and coordination [1], [15]. In project management specifically, recent work shows that digital transformation involves sociotechnical integration, governance and leadership challenges, and tensions between digital tools and existing organisational practices [15]. Within this broader context, AI can be seen as a further stage of digital transformation, moving beyond process digitalisation towards prediction, recommendation, and the partial automation of selected managerial and project activities.

For the purpose of this study, AI-enabled project management is understood as project management in which AI systems support or partially automate selected project activities, such as planning, monitoring, reporting, risk forecasting, and decision support, thereby influencing decision-making, coordination, and governance practices [8], [9], [16]. This working definition draws on established project management terminology concerning planning, monitoring, risk management, and decision support, while reflecting the growing role of AI applications across different project phases and tasks.

Existing literature reviews indicate that research on AI-enabled project management is expanding rapidly and remains primarily concentrated in specific applications, such as cost and duration prediction, risk analysis, scheduling, optimisation, and decision support [3], [4], [6], [8], [9], [17]. Earlier reviews mainly organise and classify the main areas of AI use in project contexts [4], while later studies provide broader syntheses of the field and identify emerging research gaps [3], [8], [9], [17]. More recent contributions additionally show that the literature is growing in volume but remains fragmented and strongly application-oriented [6], [9], [17]. They also provide more detailed classifications of AI techniques and their distribution across project management tasks and project phases [8], [9], [10]. Taken together, these studies show that AI is increasingly examined as a practical means of improving forecasting, control, efficiency, and decision support in projects, whereas much less attention has been paid to how these developments are theorised at a broader conceptual level.

The screening of records excluded from the core SLR dataset also suggested a strong technocentric orientation in the broader literature. This was reflected in titles and abstracts dominated by specific technologies and their applications rather than by underlying theoretical explanations. Dominant themes include Building Information Modelling (BIM), digital twins, machine learning-based optimisation, and construction-oriented digital solutions, indicating a strong focus on tools and industry-specific contexts. This pattern is consistent with recent review studies, which likewise show that research on AI-enabled project management is primarily focused on AI categories, techniques, tools, and use cases rather than on coherent theoretical integration [9], [10].

This tendency is evident across several application areas. A substantial number of studies focus on BIM-enabled coordination, lifecycle integration, and information management [18], [19], as well as digital twin and simulation-based approaches to modelling construction processes and project environments [20], [21]. At the same time, many studies use machine learning techniques for cost estimation, risk prediction, and schedule optimisation [22], [23], [24], often framing AI as a predictive or optimisation mechanism embedded in project tasks. Similarly, decision-support and optimisation models are developed to improve resource allocation and project execution efficiency [25], [26], while technologies such as blockchain and distributed ledger systems are mainly examined in relation to information transparency and data governance [27], [28]. Even in studies that address organisational or socio-technical aspects of digital transformation [29], [30], technology is typically examined through its implementation context rather than

through its theoretical implications for project management as a discipline [9], [10], [15].

This pattern reflects the applied and practice-driven character of the field, where research is primarily concerned with solving operational and technological problems within specific project settings. At the same time, this pattern reveals an important gap. Although the literature provides increasingly rich insights into what technologies are used and how they are applied, it offers much less clarity on how AI-enabled project management is theoretically explained and on the mechanisms through which AI is understood to influence project management practices, decision-making processes, and organisational dynamics [3], [7], [9], [10], [15]. In other words, current research remains much stronger in describing applications than in explaining how AI is conceptualised and theorised in relation to project management.

This gap is especially important because project management already constitutes a theoretically plural field [7], [10], [12], [13], while AI is entering project environments in multiple roles, including automation, augmentation, analytics, and control [3], [4], [6], [8], [9], [10]. Without a theory-oriented synthesis, it remains unclear how existing studies connect theoretical lenses, conceptualisations of AI, explanatory mechanisms, and levels of analysis into broader patterns of understanding. Therefore, there is a need for a more systematic and theory-focused review that moves beyond descriptive mapping of AI applications and instead explains how AI-enabled project management is theorised in the literature.

III. Materials and Methods

The study adopts a systematic literature review (SLR) to identify, map, and synthesise the theoretical foundations of AI-enabled project management research. The review was designed and conducted in line with the established PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [11], ensuring a transparent process for the identification, screening, and synthesis of theory-oriented studies in this field. Because the purpose of the review was to examine how AI-enabled project management is theorised, the search, selection, and coding strategy focused on studies that applied theoretical or conceptual perspectives to AI-enabled project management, rather than on all AI applications in project-related settings.

The literature search was conducted in the Web of Science and Scopus databases, selected as the primary sources due to their broad interdisciplinary coverage and access to high-quality and reliable academic literature.

The first literature search was conducted using a combination of keywords related to project management, theoretical components, and artificial intelligence or digital technologies. Specifically, the search string combined "project management" with terms indicating a theoretical dimension (e.g. "theor", "theoretical foundation", and "theoretical perspective") and with terms related to artificial intelligence and digital technologies (e.g. "artificial intelligence", "AI", "algorithmic", and "digital"). Several filters were also applied to refine the results, including document type, language, and years of publication. The second search round was conducted as a complementary sensitivity search to ensure that potentially relevant studies were not omitted. The subsequent stages included deduplication, title and abstract screening, and full-text eligibility assessment, all conducted in accordance with predefined decision rules described below.

The inclusion criteria were applied to identify studies that treat project management as a managerial, organisational, behavioural or governance-related domain. The exclusion criteria were established to eliminate studies in which project management was discussed primarily as a technical, application-oriented, or operational context with AI or digital technologies treated mainly as tools or optimisation methods. Studies lacking a clear theoretical grounding were also excluded. Detailed information on the search strategy for each database, the search rounds, and the identification of records is presented in Fig. 1.

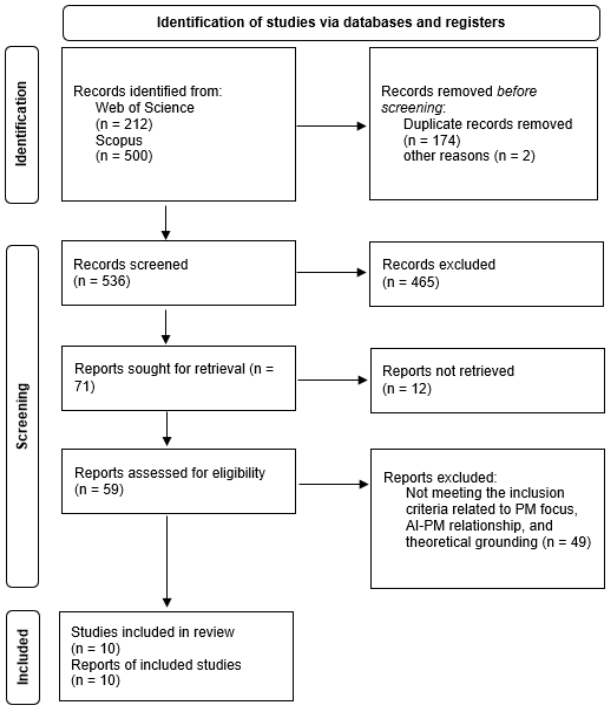

Fig. 1. PRISMA 2020 flow diagram of the study selection process

At the title and abstract screening stage, studies were retained when they addressed project management as a management discipline, linked AI or digital technologies to project management, and showed at least an explicit or implicit theoretical or conceptual signal. At the full-text eligibility stage, studies were included only when they provided an identifiable theoretical framework, conceptual model, or literature-grounded explanatory mechanism that could be extracted and coded.

Finally, to address the research objective concerning how AI-enabled project management is theorised in the literature, a structured data extraction framework was developed. The framework comprised four analytical layers: theory identification, theory positioning, conceptualisation of AI in project management, and explanatory mechanisms linking AI and project management. The coding framework was designed to make the analytical process traceable from individual studies to the higher-level synthesis of explanatory chains and emerging theoretical streams.

In the first layer, theory identification, each study was coded for its primary theory or conceptual framework, secondary theoretical perspectives, explicit or implicit use of theory, and broader theoretical lens. The coded theoretical lens was assigned according to how a theory was used in the specific reviewed study, rather than solely according to the theory's original disciplinary origin.

In the second layer, theory positioning, each study was coded according to the type of theoretical contribution and the treatment of theory. This distinction separated what kind of theoretical contribution a study claimed or produced from how theory was used, modified, developed, or integrated.

In the third layer, conceptualisation of AI, each study was coded for the dominant role or, where relevant, the combined roles attributed to AI in project management. Multiple role codes were recorded when the reviewed study clearly positioned AI in more than one way. To address the functional diversity of AI technologies, each study was also coded for the dominant or broader AI technology or function type, such as generative AI, predictive analytics, fuzzy AI, AI-enabled automation, or broader AI assimilation. This additional coding was used to support the discussion of technology-specific implications for project management.

In the fourth layer, explanatory mechanisms, each study was coded for the dominant logic through which AI was understood to influence project management. A short descriptive summary was also recorded to capture how the authors explained the role or impact of AI in project management.

Only studies meeting the full-text eligibility criteria were coded. Where studies included multiple theoretical perspectives, the dominant framework was coded as primary, while additional perspectives were recorded as secondary. Where more than one explanatory logic was present, the dominant mechanism was coded by interpreting the authors' main explanation of AI's impact on project management and assigning it to the closest fitting analytical category. Ambiguous cases were resolved through re-reading and consistency checks. The extracted data were recorded in a structured coding matrix, which served as the basis for the synthesis presented in the Result and Discussion section and Appendix.

After coding, the extracted data were compared across studies to identify recurring combinations of theoretical lenses, theories, AI roles, explanatory mechanisms, and levels of analysis. These combinations were then linked into explanatory chains. In this study, an explanatory chain is understood as an ordered analytical sequence showing how a study explains AI-enabled project management: theoretical lens – specific theory – role of AI – explanatory mechanism – level of analysis. The chains were therefore not treated as predefined categories but were developed by linking the coded elements extracted from each included study.

The synthesis proceeded in three steps. First, the coded categories were analysed separately. Second, relationships between categories were examined by linking them into explanatory chains. Third, similar chains were aggregated into recurring explanatory configurations and then grouped into emerging theoretical streams. Stream labels were assigned by comparing the dominant combination of these coded elements rather than by relying on any single category alone. These streams represent higher-level interpretive patterns in the reviewed theory-oriented literature, rather than fixed or exhaustive schools of thought. In cases where a study addressed more than one level of analysis, the relevant chain was represented at each level only when the theoretical explanation differed or when the level of analysis was substantively important for interpreting the mechanism. Therefore, the counts reported for streams should be understood as reflecting coded configurations or occurrences of explanatory patterns, rather than necessarily representing mutually exclusive categories of studies.

IV. Result and Discussion

A. Overall Literature Characteristics

A total of 712 records were identified across two search rounds. After duplicate removal, 536 records were screened at the title and abstract level. Of these, 59 records were assessed for full-text eligibility, resulting in a final sample of 10 studies [31]–[40]. The descriptive trend and journal category analysis presented below are based on all database records identified before duplicate removal and screening (n = 712), whereas the subsequent theory-oriented synthesis is based on the final sample of 10 studies.

Based on all database records identified before duplicate removal and screening (n = 712), the number of records on AI-enabled project management increased markedly after 2020 (Fig. 2). Between 2015 and 2019, the number of records remained low and relatively stable. After 2020, the number of records increased, with a marked rise in 2024 and 2025.

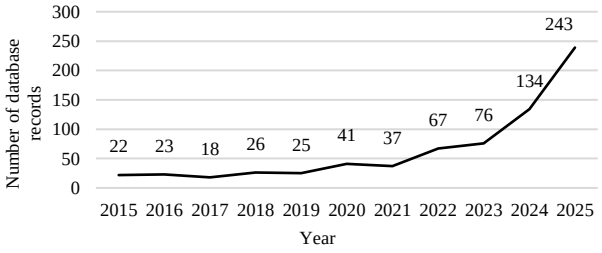

Fig. 2. Database records identified in the search by publication year (2015–2025).

In terms of study type, the final sample includes both conceptual and empirical studies. Conceptual papers represent the largest share (n = 5), followed by quantitative empirical studies (n = 4) and one mixed-method study. No purely qualitative empirical studies were identified. The distribution of final-sample studies by type of study is presented in Fig. 3.

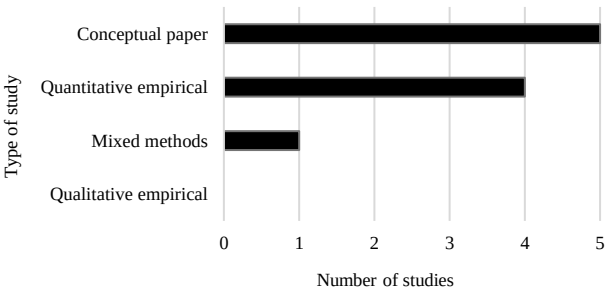

Fig. 3. Distribution of final-sample studies by type of study

Based on the same set of database records identified before duplicate removal and screening (n = 712), the analysis of journal categories shows a strong concentration of records in construction and engineering. This category accounts for 46% of all database records. Project management represents 17%, followed by AI, engineering, and technical journals (16%), and management and innovation (12%). Information systems accounts for the smallest share, at 9% of records. Each record was assigned to one dominant journal category for descriptive purposes. The percentage distribution of records by journal category is presented in Fig. 4.

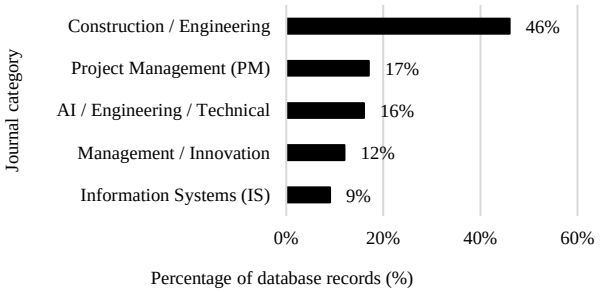

Fig. 4. Distribution of database records by journal category.

B. Theoretical Foundations of AI-Enabled Project Management

AI-enabled project management does not rely on a single theoretical foundation. Instead, the reviewed studies reveal considerable theoretical diversity. As shown in Table 1, nine studies rely on clearly identified theories [31]–[39], while one additional study applies theory only implicitly [40]. The identified theories originate from different research traditions, reflecting a mix of disciplines and perspectives. These include classical organisation and decision theories, task–technology alignment, organisational capability perspectives, complexity and social systems perspectives, as well as economic and information-based approaches. The distribution of identified theories is presented in Table 1. The remaining study [40] did not rely on a single explicitly stated theory, but reflected an implicit theoretical orientation embedded in its broader conceptual framing.

Table 1. Disciplinary origins of explicitly identified theories used in AI-enabled project management research.

Author / Year	Primary Theory Name	Disciplinary origins of theories
Felicetti et al., 2024	Adaptive Structuration Theory (AST)	Information Systems / Organisation Studies
Serra et al., 2025	Task–Technology Fit (TTF) Theory	
Kögel et al., 2025	Classical Decision Theory	Decision Sciences / Psychology
Sobchenko et al., 2024	Social Cognitive Theory	
Khan and Kwan, 2025	Dynamic Capabilities Theory	Strategic Management
Miller, 2022	Stakeholder Theory	Organisation Theory / Sociology
Kiani, 2025	Complexity Theory	
Wijayasekera et al., 2022	Information Economics Theory	Economics
Xu and Lin, 2016	Fuzzy Set Theory	Mathematics / Computer Science

The identified theories can also be grouped into several broader perspectives reflecting different ways in which AI-enabled project management is understood (see Table 2). The broader perspectives discussed below refer to theoretical traditions and should not be read as identical to the coded theoretical lens used in the synthesis. The coded lens reflects the dominant explanatory use of a theory in the specific AI-enabled project management study. The first group of studies draws on decision and behavioural theories, such as Classical Decision Theory and Social Cognitive Theory. Together, these perspectives provide an important foundation for understanding decision-making processes. In the context of AI-enabled project management, they explain how AI influences human judgement, perception and decision-making. In the analysed studies, these perspectives are further complemented by Behavioural Decision Theory and Expectancy Theory, which are used to explain individual-level decision processes.

A second group adopts a more instrumental perspective, drawing on Task-Technology Fit, Information Economics, and Fuzzy Set Theory. Task–Technology Fit explains the role of technology in terms of its alignment with specific tasks, Information Economics focuses on the value of information and its role in decision-making, and Fuzzy Set Theory addresses uncertainty and modelling in more computational terms. In the context of AI-enabled project management, these studies primarily treat AI as a tool that improves efficiency, optimises decisions, or enhances performance. In addition, Information Economics is complemented by Organisational Economics and Project Organising Theory, which are used alongside it in the analysed studies.

A third perspective is capability-based and is represented by Dynamic Capabilities Theory, which explains organisational adaptation to AI adoption through capability development. In the analysed study, AI is understood as a resource that enables organisational adaptation and development of new capabilities.

A fourth group comprises sociotechnical and organisational perspectives, such as Adaptive Structuration Theory and Stakeholder Theory. These perspectives explain how people and technology interact to shape organisational structures and ways of working, and how organisations recognise and balance the interests of different stakeholders rather than prioritising a single group. In the analysed studies, this perspective emphasises the interaction between technology and social structures, highlighting relationships, roles, and governance aspects. In addition, Adaptive Structuration Theory is used together with Task–Technology Fit (TTF), while Stakeholder Theory is complemented by Role Theory.

The final group is represented by Complexity Theory, which explains how systems with many interacting elements behave in unpredictable ways. This perspective emphasises the need for adaptive and non-linear approaches to management. In the analysed study, AI is framed as a mechanism that helps organisations manage uncertainty and dynamic environments.

Table 2. Primary and secondary theories used in AI-enabled project management studies.

Group	Primary Theory Name	Secondary Theory Name (if applicable)
1	Classical Decision Theory	Behavioural Decision Theory
	Social Cognitive Theory	Expectancy Theory
2	Task–Technology Fit (TTF) Theory	–
	Fuzzy Set Theory	–
	Information Economics Theory	Organisational Economics Theory Project Organising Theory
3	Dynamic Capabilities Theory	–
4	Adaptive Structuration Theory (AST)	Task–Technology Fit (TTF) Theory
	Stakeholder Theory	Role Theory
5	Complexity Theory	–

Although Table 1 reports explicitly identified primary theories and Table 2 reports explicitly identified primary and secondary theories, the subsequent configuration analysis retained the implicit sociotechnical orientation identified in study [40], as it provided a codable explanatory mechanism linking AI and project management.

The analysis distinguished between theoretical contribution and theoretical treatment. In terms of theoretical contribution, theory testing (n = 3) and theory building (n = 3) were the most common forms, followed by conceptual development (n = 2), theory application (n = 1), and theory extension (n = 1). No study was classified as theory integration as its primary type of theoretical contribution. In terms of theoretical treatment, most studies applied existing theories without substantial modification (n = 5), while a smaller number developed (n = 3) or reframed (n = 2) existing theoretical perspectives. This distribution of theoretical treatment is presented in Fig. 5.

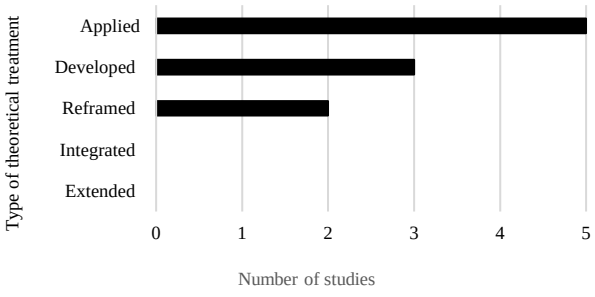

Fig. 5. Distribution of studies by theoretical treatment.

C. *Conceptualisation and Explanatory Mechanisms of AI-enabled Project Management*

The analysis of the role of AI in project management shows a clear dominance of decision-support and augmentation perspectives, each represented by four coded AI-role assignments (Fig. 6). In contrast, AI as a task-specific support tool appears less frequently, with two coded assignments. Other perspectives, such as AI as an organisational capability or as a sociotechnical system, are only marginally represented, each appearing in one coded assignment. No coded assignments conceptualise AI as a governance mechanism or as digital infrastructure. Some studies conceptualised AI in more than one way. Therefore, the categories in Fig. 6 should be interpreted as coded AI-role assignments rather than mutually exclusive study-level categories.

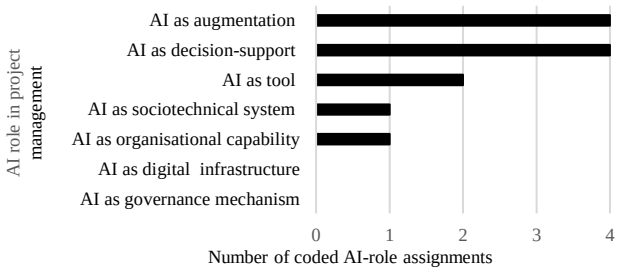

Fig. 6. Distribution of coded AI-role assignments.

A further distinction concerns the type or function of AI technology examined in the reviewed studies. Some studies examine relatively specific AI technologies or functions, such as generative chatbots, fuzzy AI, predictive analytics, or AI-driven monitoring systems. Others use AI more broadly to describe organisational assimilation, capability development, or sociotechnical change.

The analysis of explanatory mechanisms linking AI and project management shows a clear dominance of instrumental perspectives, identified in four studies (Fig. 7). Adoption-oriented mechanisms appear in two studies, suggesting that some research focuses on how AI is accepted and used by project members. Capability-enhancing, governance-restructuring, sociomaterial co-agency and complexity-adaptive perspectives are only marginally represented, each appearing in a single study.

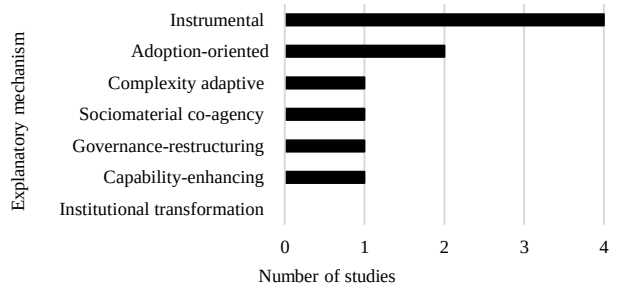

Fig. 7. Distribution of studies by explanatory mechanisms of AI impact on project management.

D. *Explanatory Chains and Emergence of Theoretical Streams*

The analysis of explanatory chains shows that studies follow recurring configurations when explaining AI-enabled project management. The most frequent configurations combine decision / behavioural lens with specific theories, including Classical Decision Theory, Fuzzy Set Theory, Information Economics and Social Cognitive Theory. Within these configurations, AI is most often assigned the role of decision-support or augmentation. The associated explanatory mechanisms are primarily instrumental or adoption-oriented, with levels of analysis located at the project, organisational, or individual level (Fig. 8).

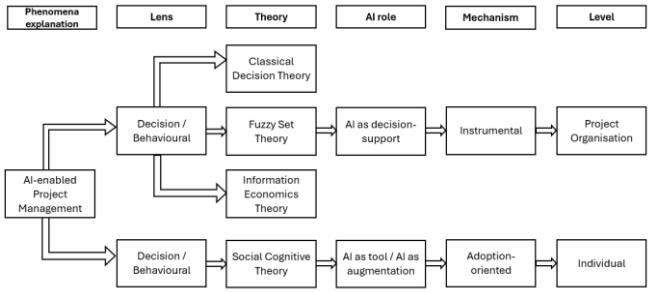

Fig. 8. Explanatory chains within the decision / behavioural lens in AI-enabled project management.

Fig. 9 presents a combined view of the main explicitly theorised explanatory chains identified across the reviewed studies. The figure integrates the different configurations linking theoretical lenses, theories, AI roles, mechanisms, and levels of analysis. It shows that multiple pathways are used to explain AI-enabled project management. Different lenses are associated with different theories and lead to different combinations of AI roles, mechanisms, and levels of analysis. At the same time, some elements appear across more than one pathway, indicating partial overlap between the configurations. The implicit sociotechnical configuration identified in study [40] is not shown as a separate pathway in Fig. 9, because it does not rely on a named primary theory. It was retained in the synthesis and is reported separately in Fig. 13 and Table A1 as a sociotechnical / co-agency stream.

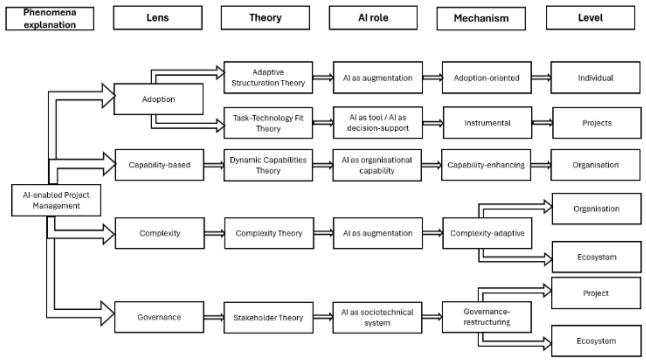

Fig. 9. Combined representation of explanatory chains linking theoretical lenses, theories, AI roles, mechanisms, and levels of analysis in AI-enabled project management.

The analysis of how theory is used within these chains shows that theoretical lenses and theories are most often combined in recurring ways. The most common pattern links the decision / behavioural lens with Classical Decision Theory and Social Cognitive Theory, while another recurrent pattern connects an adoption-oriented lens with Adaptive Structuration Theory and Task–Technology Fit Theory. These patterns are illustrated in Fig. 10 and Fig. 11.

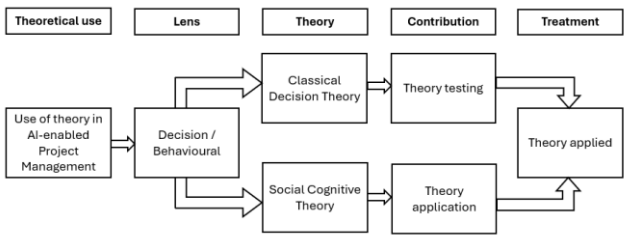

Fig. 10. Theoretical use: application of existing theories within decision / behavioural lens

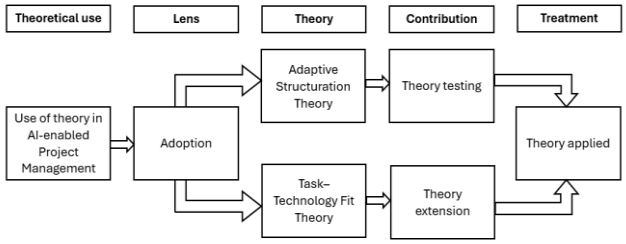

Fig. 11. Theoretical use: application of existing theories within adoption lens

The analysis also identifies less frequent configurations in which theories are conceptually reframed or further developed. In these cases, complexity and governance lenses are linked with Complexity Theory and Stakeholder Theory. These configurations are associated with conceptual development or theory building, and with forms of theoretical treatment involving reframing or development. These patterns are illustrated in Fig. 12.

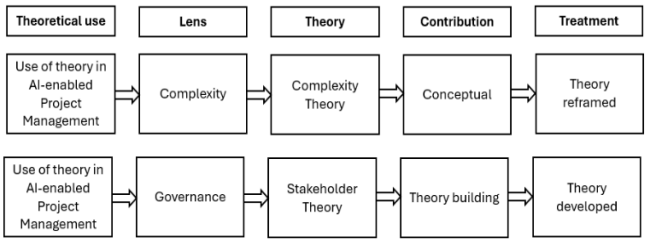

Fig. 12. Theoretical use: reframing and developing existing theories within complexity and governance lenses.

Finally, by aggregating the identified configurations across theoretical lenses, AI roles, mechanisms, and levels of analysis, several broader theoretical streams were identified. The most frequent stream is decision-support / instrumental (n = 6). Additional streams include governance / sociotechnical (n = 2), adoption-oriented (n = 2), complexity-adaptive (n = 2), capability-based (n = 1), and sociotechnical / co-agency (n = 1). One implicit sociotechnical configuration was retained as a separate sociotechnical / co-agency stream because study [40] did not apply a named primary theory but provided an identifiable explanation of human–AI collaboration, trust, and AI-enabled transformation in project management. The distribution of these streams across coded configurations is presented in Fig. 13. Detailed configurations explaining the identified streams are presented in Table A1 in the Appendix.

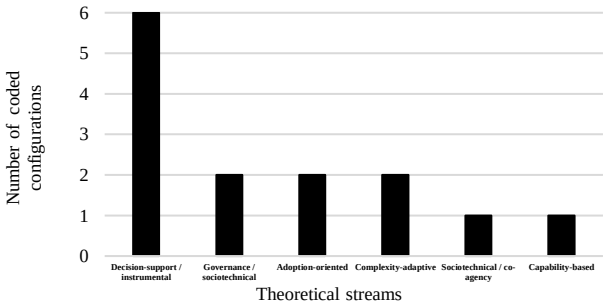

Fig. 13. Distribution of emerging theoretical streams across coded configurations.

CONCLUSION

This study set out to examine how AI-enabled project management is theorised in the existing literature. As the literature review demonstrated, existing research on AI-enabled project management draws on a wide range of theoretical perspectives originating from diverse disciplines, including organisation studies, decision sciences, strategic management, information systems, and economics. These perspectives include, among others, decision and behavioural theories, task-technology alignment perspectives, capability-based views, sociotechnical approaches, stakeholder theory and complexity theory. While this diversity indicates the richness of the field, the review also reveals that existing studies tend to adopt theories in an isolated and instrumental manner, often focusing on explaining specific aspects of AI use, such as decision support. Less attention is given to alternative conceptualisations, such as AI as an organisational capability, a sociotechnical system, or a governance mechanism. This limited presence suggests that important dimensions of AI-enabled project management, including issues of power, coordination, accountability, and emergent behaviour, are not yet sufficiently theorised.

Building on these observations, this study moves beyond a descriptive synthesis of theories by identifying recurring explanatory chains that link theoretical lenses, specific theories, conceptualisations of AI, explanatory mechanisms, and levels of analysis. These chains reveal that theorisation in AI-enabled project management follows identifiable patterns. They were further aggregated into broader theoretical streams, which show how different combinations of lenses, theories, AI roles, mechanisms, and levels of analysis structure current theory-oriented knowledge in this field.

The reviewed studies also show that AI-enabled project management does not refer to one uniform type of technology. Some studies examine relatively specific AI tools or functions, such as ChatGPT, generative chatbots, fuzzy AI models, predictive analytics, or AI-driven monitoring systems. In these cases, the implications for project management are mainly task-specific and concern communication, information processing, decision support, scheduling, risk prediction, monitoring, or quantitative decision-making. Other studies discuss AI more broadly as an organisational capability, an assimilation process, or a sociotechnical system. These studies shift attention from individual tools to agility, trust, accountability, stakeholder inclusion, ethics, and human-AI collaboration. This distinction matters because the implications of AI for project management depend not only on the theoretical lens used, but also on the type, function, or broader conceptualisation of AI examined in the study.

The main contribution of this study lies in advancing a configurational understanding of theorisation in AI-enabled project management. Rather than treating theories as isolated analytical tools, the study demonstrates that they operate as part of broader explanatory configurations. By uncovering these configurations and synthesising them into emerging theoretical streams, the paper provides a structured account of how knowledge in this domain is currently produced and organised.

The findings suggest that AI-enabled project management is still theorised unevenly, with stronger attention to decision support and instrumental mechanisms than to governance, accountability, and sociotechnical change. Future research should therefore focus more strongly on theory development in AI-enabled project management, especially through adapting existing theories, comparing and integrating different theoretical perspectives, and developing more specific explanations of how AI reshapes project management. In addition, the theoretical streams identified in this review should be further examined and validated on broader empirical material and across different project contexts. In particular, greater attention is needed to governance mechanisms, human-AI interaction, and the emergent properties of complex project environments. Such efforts would contribute to advancing a more comprehensive understanding of AI in project management. Future studies could also compare how different AI technologies and functions affect project management roles, decision-making processes, coordination practices, and organisational capabilities across different project contexts.

Several limitations should be acknowledged. First, the final sample consisted of 10 theory-oriented studies, which limits the generalisability of the findings. This reflects the review's strict eligibility criteria and means that the identified explanatory configurations and theoretical streams should be interpreted as emerging patterns rather than definitive classifications of the field. Second, the coding process required interpretive judgement, particularly when assigning studies to theoretical lenses, AI roles, explanatory mechanisms, and levels of analysis. Although structured coding rules, re-reading, and consistency checks were used, the findings should be understood as an analytical synthesis rather than a statistically generalisable mapping. Third, the coding of AI technology / function types should also be interpreted cautiously, because the reviewed studies differed in how specifically they described AI technologies. Future research should validate and refine both the identified theoretical streams and the AI technology / function distinctions using broader datasets and empirical studies across different project contexts.

APPENDIX A

Table A1. Configurations of theoretical lenses, AI roles, AI technology / function types, mechanisms, and levels of analysis.

Theoretical Lens	Theory	Role of AI in project management	AI technology / function types	Mechanism	Level of Analysis	Stream
Adoption	Adaptive Structuration Theory	AI as augmentation	Generative AI / ChatGPT / chatbot	Adoption-oriented	Individual	Adoption-oriented

Adoption	Task–Technology Fit Theory	AI as a tool AI as decision-support	Patent-based data-centric AI / predictive analytics / optimisation	Instrumental	Project	Adoption-oriented
Capability-based	Dynamic Capabilities Theory	AI as organisational capability	AI assimilation / AI-enabled analytics / predictive capabilities	Capability-enhancing	Organisation	Capability-based
Complexity	Complexity Theory	AI as augmentation	Mixed AI ecosystem: ML / NLP / predictive analytics / AI-enabled decision support	Complexity-adaptive	Organisation	Complexity-adaptive
Complexity	Complexity Theory	AI as augmentation	Mixed AI ecosystem: ML / NLP / predictive analytics / AI-enabled decision support	Complexity-adaptive	Ecosystem	Complexity-adaptive
Decision / Behavioural	Classical Decision Theory	AI as decision-support	Generative AI / ChatGPT3.5 / hybrid decision-making	Instrumental	Project	Decision-support / instrumental
Decision / Behavioural	Social Cognitive Theory	AI as a tool AI as augmentation	AI-driven operational tools: data analytics / automation / predictive maintenance / emergency decision support	Adoption-oriented	Individual	Decision-support / instrumental
Decision / Behavioural	Fuzzy Set Theory	AI as decision-support	Fuzzy AI / fuzzy inference / knowledge-based decision support	Instrumental	Project	Decision-support / instrumental
Decision / Behavioural	Fuzzy Set Theory	AI as decision-support	Fuzzy AI / fuzzy inference / knowledge-based decision support	Instrumental	Organisation	Decision-support / instrumental
Decision / Behavioural	Information Economics Theory	AI as decision-support	Data analytics / predictive AI / digital project delivery infrastructure	Instrumental	Project	Decision-support / instrumental
Decision / Behavioural	Information Economics Theory	AI as decision-support	Data analytics / predictive AI / digital project delivery infrastructure	Instrumental	Organisation	Decision-support / instrumental
Governance	Stakeholder Theory	AI as sociotechnical system	Algorithmic decision-making / autonomous AI systems / AI projects	Governance-restructuring	Project	Governance / sociotechnical
Governance	Stakeholder Theory	AI as sociotechnical system	Algorithmic decision-making / autonomous AI systems / AI projects	Governance-restructuring	Ecosystem	Governance / sociotechnical
Sociotechnical	Implicit sociotechnical orientation / no primary theory	AI as augmentation	Hybrid PM2030 AI portfolio: GenAI / predictive AI / automation / human–AI collaboration and trust	Sociomaterial co-agency	Organisation	Sociotechnical / co-agency

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Both authors contributed significantly to the development of this manuscript. Alina Kozarkiewicz was responsible for the conceptualisation of the study, development of the framework, and supervision of the research process. Anna Mazur conducted the data collection and analysis and drafted the initial version of the manuscript. Both authors contributed to the interpretation of the results, critically revised the manuscript for important intellectual content, and approved the final version for publication.

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References

[1] G. Vial, “Understanding digital transformation: A review and a research agenda,” The Journal of Strategic Information Systems, vol. 28, no. 2, pp. 118–144, Jun. 2019.

[2] Y. K. Dwivedi et al., “Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy,” International Journal of Information Management, vol. 57, Art. no. 101994, Apr. 2021.

[3] R. Müller et al., “Artificial intelligence and project management: Empirical overview, state of the art, and guidelines for future research,” Project Management Journal, vol. 55, no. 1, pp. 9–15, Feb. 2024.

[4] I. Taboada et al., “Artificial intelligence enabled project management: A systematic literature review,” Applied Sciences, vol. 13, no. 8, Art. no. 5014, Apr. 2023.

[5] S. Kraus et al., “Digital transformation in business and management research: An overview of the current status quo,” International Journal of Information Management, vol. 63, Art. no. 102466, Apr. 2022.

[6] S. Salimimoghadam et al., “The rise of artificial intelligence in project management: A systematic literature review of current opportunities, enablers, and barriers,” Buildings, vol. 15, no. 7, Art. no. 1130, Apr. 2025.

[7] T. P. Kenworthy and K. Jugdev, “What do we really know? A 40-year scientific realist examination of theory testing in project management,” International Journal of Project Management, vol. 43, no. 8, Art. no. 102788, Nov. 2025.

[8] D. S. Adamantiadou and L. Tsironis, “Leveraging artificial intelligence in project management: A systematic review of applications, challenges, and future directions,” Computers, vol. 14, no. 2, Art. no. 66, Feb. 2025.

[9] M. Khalil et al., “Mapping the AI landscape in project management context: A systematic literature review,” Systems, vol. 13, no. 10, Art. no. 913, Oct. 2025.
[10] J. Geraldi and J. Söderlund, “Project studies: What it is, where it is going,” International Journal of Project Management, vol. 36, no. 1, pp. 55–70, Jan. 2018.
[11] M. J. Page et al., “The PRISMA 2020 statement: An updated guideline for reporting systematic reviews,” BMJ, vol. 372, Art. no. n71, Mar. 2021.
[12] J. Söderlund, “Building theories of project management: Past research, questions for the future,” International Journal of Project Management, vol. 22, no. 3, pp. 183–191, 2004.
[13] S. Cicmil et al., “Rethinking project management: Researching the actuality of projects,” International Journal of Project Management, vol. 24, no. 8, pp. 675–686, 2006.
[14] C. Marnewick and A. L. Marnewick, “Digitalization of project management: Opportunities in research and practice,” Project Leadership and Society, vol. 3, Art. no. 100061, Dec. 2022.
[15] M. Chen et al., “Digital transformation in project management: A systematic review and research agenda,” Systems, vol. 13, no. 8, Art. no. 625, Aug. 2025.
[16] Project Management Institute, A Guide to the Project Management Body of Knowledge (PMBOK® Guide) and The Standard for Project Management, 8th ed. Newtown Square, PA: Project Management Institute, 2025.
[17] M. E. Nenni et al., “How artificial intelligence will transform project management in the age of digitization: A systematic literature review,” Management Review Quarterly, vol. 75, no. 2, pp. 1669–1716, Apr. 2024.
[18] Z. Ye et al., “Building information modeling (BIM) in project management: A bibliometric and science mapping review,” Engineering, Construction and Architectural Management, vol. 32, no. 5, pp. 3078–3103, May 2025.
[19] Y. Liu et al., “Integration of building information modeling (BIM) with transportation and facilities: Recent applications and future perspectives,” Buildings, vol. 14, no. 2, Art. no. 541, Feb. 2024.
[20] F. Wang et al., “An LLM-guided SD-LDM Digital Twin Construction Strategy (LSDT) for multi-industrial scenarios: Enhancing adaptability and efficiency,” Journal of Manufacturing Systems, vol. 80, pp. 995–1012, Jun. 2025.
[21] R. Sacks et al., “Construction with digital twin information systems,” Data-Centric Engineering, vol. 1, Art. no. e14, Jan. 2020.
[22] B. Wang, J. Yuan, and K. Z. Ghafoor, “Research on Construction Cost Estimation based on Artificial Intelligence Technology,” Scalable Computing: Practice and Experience, vol. 22, no. 2, pp. 93–104, Oct. 2021.
[23] J. Wang et al., “Construction cost prediction using a fused loss-enhanced hybrid GCN–GAT–MLP approach,” Engineering, Construction and Architectural Management, pp. 1–24, Dec. 2025.
[24] F. Mostofi et al., “Construction delay prediction model using a relationship-aware multihead graph attention network,” Journal of Management in Engineering, vol. 41, no. 3, Feb. 2025.
[25] J. B. Sarmento dos Santos-Neto and A. P. C. S. Costa, “A multi-criteria decision-making model for selecting a maturity model,” International Journal of Decision Support System Technology, vol. 15, no. 1, pp. 1–15, Jan. 2023.
[26] M. S. Islam et al., “A coupled genetic programming Monte Carlo simulation–based model for cost overrun prediction of thermal power plant projects,” Journal of Construction Engineering and Management, vol. 148, no. 8, Art. no. 04022073, Aug. 2022.
[27] S. Ding et al., “Secure and formalized blockchain-IPFS information sharing in precast construction from the whole supply chain perspective,” Journal of Construction Engineering and Management, vol. 150, no. 1, Art. no. 04023150, Jan. 2024.
[28] J. Li et al., “Blockchain in the built environment and construction industry: A systematic review, conceptual models and practical use cases,” Automation in Construction, vol. 102, pp. 288–307, Jun. 2019.
[29] P. Barthel and T. Hess, “Towards a characterization of digitalization projects in the context of organisational transformation,” Pacific Asia Journal of the Association for Information Systems, vol. 12, no. 3, pp. 31–56, Sep. 2020.
[30] M. Rogers et al., “Stakeholder engagement with funding bodies, steering committees and surveys: Benefits for education projects,” Issues in Educational Research, vol. 32, no. 3, pp. 1131–1152, Sep. 2022.
[31] A. M. Felicetti et al., “Artificial intelligence and project management: An empirical investigation on the appropriation of generative Chatbots by project managers,” Journal of Innovation & Knowledge, vol. 9, no. 3, Art. no. 100545, Jul. 2024.
[32] F. A. R. Serra et al., “Artificial intelligence in project management: An analysis of patent trends and task-technology fit,” International Journal of Innovation, vol. 13, no. 3, Art. e28348, 2025.
[33] D. Kögel, S. Meile, and L. Canos-Daros, “Who’s Steering Whom and in What Direction? An Experiment on AI Versus Top Management Decision-Making in Projects,” Project Management Journal, vol. 57, pp. 1–17, 2025.
[34] V. Sobchenko et al., “Artificial intelligence for enhancing engineering project management during emergencies: Perception-based analysis,” Quality Innovation Prosperity, vol. 28, no. 3, pp. 46–62, 2024.
[35] A. N. Khan and H. K. Kwan, “AI, Agility, and Environmental Performance: A New Framework for Construction Project Managers,” Journal of Construction Engineering and Management, vol. 151, no. 3, Art. no. 04025003, 2025.
[36] G. J. Miller, “Stakeholder roles in artificial intelligence projects,” Project Leadership and Society, vol. 3, Art. no. 100068, 2022.
[37] A. Kiani, “Artificial intelligence in entrepreneurial project management: a review, framework and research agenda,” International Journal of Managing Projects in Business, vol. 18, no. 4/5, pp. 708–720, 2025.
[38] S. C. Wijayasekera et al., “Data analytics and artificial intelligence in the complex environment of megaprojects: Implications for practitioners and project organizing theory,” Project Management Journal, vol. 53, no. 5, pp. 485–500, 2022.
[39] F. Xu and S.-P. Lin, “Theoretical framework of Fuzzy-AI model in quantitative project management,” Journal of Intelligent & Fuzzy Systems, vol. 30, no. 1, pp. 509–521, 2016.
[40] L. Hughes et al., “Impact of artificial intelligence on project management (PM): Multi-expert perspectives on advancing knowledge and driving innovation toward PM2030,” Journal of Innovation & Knowledge, vol. 10, Art. no. 100772, 2025.

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