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Towards Project Management 5.0: The role of artificial intelligence, human-centric decision-making, and sustainability in project success—An empirical study from Jordan

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A B S T R A C T

Project Management 5.0 takes the perspective of viewing AI as a value-creating capability, arguing that it needs to be under human-centric governance, built with sustainability principles. In this study, we presumed after examining the impacts of AI adoption on project success and the intervening variables of human-centric decision-making (HCDM) and sustainability integration (SUS). The gathered data from 384 project professionals from the major sectors in Jordan were analysed using SPSS 29 and Smart PLS 4 software. Results indicate that the use of AI has a positive direct effect on project success ($\beta = 0.284$, $p < 0.001$) and indirect effect on project success through HCDM (indirect effect = 0.203), and SUS (indirect effect = 0.171). Adopting the model explains 58.7% of the success variance in projects and supports complementary incomplete mediation. The study empirically operationalises the definition of PM 5.0 as an AI–human–sustainability framework and offers new empirical evidence in the context of a developing economy.

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1. Introduction

The project economy is in a big transformation. The business logic of Industry 4.0 has directed the past decade of digital project management, placing the emphasis on technological advances and their impact on automation, efficiency, prediction and process control. However, project planning, scheduling, risk assessment, allocation of resources, and stakeholder management (Bachari et al., 2025; Nenni et al., 2025; Taboada et al., 2023) have increasingly become helped by artificial intelligence (AI), advanced analytics and increasingly autonomous systems. However, the new Industry 5.0 paradigm introduces a new concept that suggests that just having cutting-edge tech and efficient operations doesn't inevitably mean progress is being made. Rather, it treats technological advance as a key aspect of the value creation for the organization, but also human centricity, sustainability and resilience. The switch has implications for project management. Projects are not just a transportation vehicle for technology; they are a temporary organization where technology, human judgement, and stakeholders' interests and the environment and social responsibility continuously interact. As a follow, there arises a question which goes beyond the ability of AI to optimize schedules, predict outcomes, or improve resource usage, when and how does AI drive real project success and sustainability in an organization? The question increases significance the more the usage of AI shifts from being a peripheral technology for decisions to a more structural one for project governance and managerial

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decisions as AI emerges from being just another peripheral decision support tool to playing a more integral role in managerial decisions (Almeida et al., 2025; Felicetti et al., 2024; Hughes et al., 2025).
Recent studies show significant hope for AI in project management. Recent studies show great promise in the field of AI-powered project management. AI can reinforce forecasting models, detect potential threats, assist with resource allocation, streamline repetitive administrative tasks, and aid in managing intricate project data (Bachari et al., 2025; Nenni et al., 2025; Taboada et al., 2023). AI has greater capabilities even more by providing capabilities for communication, documentation, knowledge sharing and managerial problem solving, as is now made possible by generative AI (Felicetti et al., 2024). But this increasingly complicated technological picture also reveals a major problem in present literature. The range of presented research largely assumes that more capable technology will lead to better outcomes in projects. This techno-centric reading omits to account for the organization of the “work” of algorithmic outputs, the processes and interactions in which they are recited, challenged, put into context, and as a result, put into practice as managerial action.

This is a crucial constraint, especially since AI can't change human judgment. Instead, its growing analytical power could make more-skilled human skills, like being able to interpret in context, think ethically, be concerned for stakeholders, be held accountable, and make judgments of uncertainty more valuable. For instance, Barcaui and Monat (2023) found that generative AI can generate planning outputs that are like that of a project manager but underline the key limitations when contextual and managerial judgement is needed. Likewise, Felicetti et al. (2024) demonstrate that project managers are exceedingly entrepreneurial entrepreneurs of generative AI technologies, and that having a “technology functionality” does not necessarily guarantee that the technology is strategically integrated into project practices. This information reveals that the utility of AI could not be confined to the replacement of managerial decision-making but rather be used as a complement to it.

In this complementary capability, we refer to the view of human-centric decision-making (HCDM). In an Industry 5.0 framework, the HCDM is an organizational structure that considers the intelligence provided by AI without replacing the need for human agency, ethical consideration, sensitivity to stakeholders, and managerial accountability. This separation, in theory, has repercussions. Human centricity is not meant to be an antipode to automation but rather should be taken as deliberate reconfiguration of technological and social capabilities ensuring computational intelligence does not take the place of the human judgement but enhances it (Dani et al., 2026; Martini et al., 2024). This way, AI could progress project success by allowing management to free up mental capacity from repetitive analytical work toward interpretation, relationship management, ethical analysis and strategic decision-making.

Similarly, in the sustainability arena a parallel change is taking place. Traditional measures for projects' success are often those of efficiency: time, cost, scope, and quality. While these dimensions are still appropriate, projects' contribution to the environment and society and their longer-term economic impact are becoming increasingly important in today's day and age for project governance. Sustainability has thus budged from being a corporate responsibility issue on the margins to being a core element of project objectives, governance structures, resource choices, and success measures (Mahgoub & Yu, 2026; Silvius et al., 2025). AI can now help this shift by enhancing environmental monitoring, optimization of resources, emissions monitoring, scenario analysis, and data-driven sustainability decisions (Demeke, 2025; Jariwala, 2024).

Most importantly, sustainability is not just another goal that AI can contribute to but is an elementary and necessary component of the entire value chain. It can also serve as a governance framework to steer AI-powered capabilities towards sustained project value. For example, alhammadi (2025) said that technological innovation's performance impacts are partly conveyed through sustainability culture and managerial support. This indicates technology resources have no performance value without being motivated by organizational orientations. The other way in which AI is being translated to project success may therefore be ‘Sustainability integration’: while human-centric decision making is the reason for the algorithmic intelligence to be agreed a beat, Sustainability integration is the reason for the algorithmic intelligence to be given a direction, one that is guided by sustainability goals, environment, social, and economic.

All the above indicate a promising meaning of Project Management 5.0 (PM 5.0). The challenges in this study are not simply about adopting advanced AI into the existing project-management workflow, but about actively embedding AI capability, human decision making and sustainability thinking into a rounded project-governance framework. All three are complementary rather than competitive, AI enhances analytical intelligence, human-centric decision-making guarantees responsibility, judgement and stakeholder legitimacy, and sustainability integration focuses technology and managerial capacities on long-term value creation. Thus, PM 5.0 is a paradigm change in the sense of moving from technology addressed optimization to the orchestration of human, technology and sustainability.

Although conceptual evidence of this type of orientation has been encouraged, the empirical literature is still dispersed. Three gaps are of special significance. Firstly, there is a gap between the operationalization. Previous research and studies on project-management and AI in the Industry 5.0 era are largely systematic reviews, conceptual discussions, expert voices, and technology-based classifications (Nenni et al., 2025; Bachari et al., 2025; Hughes et al., 2025; Dani et al., 2026). PM 5.0 is therefore still a durable “story” than an “organizational model” that is grounded in experience. It is less clear whether the concepts of 'operationalizing' these key building blocks of sustainable development, AI adoption, human centricity and sustainability, as interconnected and interconnected concepts can be treated within a single nomological frame.

Secondly, there is space in the mechanism. Some existing studies indicate that AI and technological innovation can improve various project performance features but offer little detail on how these impacts happen (Alhammadi, 2025; Taboada et al., 2023). Organizational processes in effect transforming technological capability to project value may be masked in direct effect models. This is a significant omission in theory since, if AI is a technological resource but not a goal, the outcome impacts of AI could be shaped by supporting managerial and organizational processes. This transfiguration could take place in two different, although theoretically complementary, ways: via HCDM or via sustainability integration.

Thirdly, literature shows a 'contextual imbalance.' But much of the empirical knowledge of AI-powered project management has come from technologically advanced or reasonably better-resourced settings. Even though they have different mixes of institutional capacity, maturity of digital landscape, availability of skills, financial resources, and sustainability challenges, developing economies continue to be significantly underrepresented. This geographical imbalance hinders the facility to generate a comprehensive grasp of the extent to which emerging PM 5.0 principles are valid organizational processes across all contexts or just those of the advanced economy context.

Jordan offers a very educational backdrop around which to discuss this issue. It is a nation with a bold digital-transformation and sustainability strategy, as well as some of the resources, capacity and institutional challenges typical of developing countries. The company's miscellaneous project scope includes modules from construction and engineering, information technology and telecommunications, banking and financial services, and manufacturing, all of which result in a speckled environment where AI application and sustainability concerns converge. Previous research in Jordan revealed that existing project management skills, particularly scope management, time management, cost management and quality management, play a significant role in the effectiveness of organisations (Kilani et al., 2024). However, empirical literature is regulated in terms of building links between the capabilities enabled by AI and human judgement and the role of sustainability-focused governance in a project's success in this context.

RQ1: What is the relationship between AI use and project success? RQ2: What are the major attributes of projects that are successful when using AI? Does human-centric decision-making and sustainability integration lie between the adoption of AI and productive projects? RQ3: In a developing economy context what do these relationships tell of the emerging architecture of Project Management 5.0?

To address these questions, the study proposes and empirically validates the dual-mediation model that shows the relationship between the adoption of AI and project success both unswervingly and indirectly by human-centric decision-making and sustainability integration. The model takes into account the complementarity between the technological and the human subsystems of the sociotechnical system (as explained by the theory of sociotechnical systems), it considers how technological resources are curved into organizational value through complementary capabilities (dynamic capabilities perspective), and it considers that the project value is not just short-term efficiency but also environmental, social and economic sustainability (triple-bottom-line logic).

This study is of several main contributions. First, it takes the construct of PM 5.0 from a rhetoric to an operationalization level by modeling the adoption of AI, human-centric decision making, sustainability integration, and project success in an integrated framework. Second, it splits from the prevailing logic of direct transmission of AI research that focuses on the direct impacts of AI capability and recognizes two other transmission mechanisms for endeavor value creation, namely, personalization and assessment. In this way, the study helps to move the discussion of AI in project management away from 'automation' towards 'augmentation'. Thirdly, it incorporates technological, behavioral and sustainability views traditionally developed in distinct research disciplines, thus bringing the concept of PM 5.0 to the fore as a capability architecture with a triadic nature instead of a set of independent practices. Fourth, the study causes evidence from Jordan to the geographic boundaries of research on an AI for project management and explores the potential relevance of mechanisms of PM 5.0 in a resource-constrained and digitally immature environment.

The core argument of this paper is relaxed to state but has important theoretical implications: Project value is not added by AI. Its contribution relies on the architecture of the organization in which the computational intelligence is explained and steered. In addition to sustainability integration, providing purpose, horizon and value orientation, human-centric decision-making requires judgement, accountability and legitimacy. Project Management 5.0 is built not just from technological sophistication, but from the orchestration of these capabilities!

The remainder of this paper follows as follows: Section 2 builds theoretical foundations and critically reviews and integrates literature on AI-supported project management, human-centric decision-making and integration of sustainability. The conceptual model and hypotheses are displayed in section 3. The research design and analytical processes are described in Section 4. The empirical results are discussed in Section 5. The findings and theoretical implications are discussed in Sections 6 and 7, and the practical implications, limitations, and future research directions in Sections 8 and 9. Finally, the implications of the proposed PM 5.0 architecture for the developing project economy are examined.

2. Theoretical Background and Critical Narrative Review

2.1 From Industry 4.0 to Industry 5.0: Redefining the Project Paradigm

Industry 4.0 to 5.0 is more than a step in technology development; it's an altering of the reason for using technology. The main theme of Industry 4.0 was cyber-physical integration, automation, interoperability, real-time data exchange and efficiency. In project management, this reasoning demonstrated itself in digitally supported planning, automated timing, forecast-based cost management and control, integrated reporting, and increasingly data-based decision making. Such advances greatly adjusted the technical competence of Project Organizations; They also fostered an efficiency-oriented view of a successful project, and it is likely that technological complexity was sometimes taken as a form of success.

Industry 5.0 contradicts this notion by modifying the value of technological capability to the larger context of human, social and environmental value creation. Instead of contrasting the technological progress of "Industry 4.0", it takes into consideration the purpose of the technological tools: intelligent technologies, and the related ones, should support humans in the execution of their work, support sustainability and reinforce organizational and social resilience (Dani et al, 2026; Martini et al, 2024). This difference is especially relevant to project management, since projects are short-lived organizational processes in which long term value objectives, the restrictions on their ability to deliver them, stakeholders' expectations for them, human judgement, and technology all come together.

As assessed from this angle, project management should progress from a delivery-based discipline to a value stewardship discipline in the era of industry 5.0. For Dani et al. (2026), this transition will demand increased focus on human-centeredness, sustainability and resilience, as well as technological progress. Similarly, Martini et al. (2024) focus on the concept of human-centered and sustainable AI, suggesting that it should be combined as a design principle, not as a reaction to the implementation of technological systems. Their argument highlights a significant drawback of AI designed with an exclusive focus on optimization: algorithms can be exceedingly effective at optimizing set goals but be completely oblivious to issues that do not fit into the goals, such as ethical or social or stakeholder or environmental concerns.

The transition is, however, not conceptually as mature as is demonstrated. There is a link between technology, collaboration, and sustainability, as they can contribute to resilience and efficiency when combined in the right way, as noted by Mahgoub and Yu (2026); while Hughes et al. (2025) focus upon the complementary knowledge, governance and innovation capabilities required for the future of AI in project management. All these studies suggest that advanced technology does not just happen to be valuable but is contingent upon it. However, literature offers significantly more normative arguments for the reality of Industry 5.0 than empirical evidence on the interaction of the components of Industry 5.0 within project organizations.

This creates a conflicting rhetorical focus in the changing research: on the one hand, the values of Industry 5.0 are introduced; on the other hand, the assumptions of Industry 4.0 remain statistically significant. The notions of human centricity, sustainability and resilience are being promoted and discussed increasingly, but often technology is studied separately from the structure of the organization's processes and procedures that will realize it in the value of the project. The tension is then used to further develop this concept by proposing an integrated capability architecture for Project Management 5.0 (PM 5.0), where artificial intelligence is coupled with human-centered decision making and sustainability integration. The theoretical question has thus transferred from the technological sophistication of projects to human-centered, sustainable and hence successful project outcomes.

2.2 Artificial Intelligence in Project Management: Opportunities and Critical Tensions

Artificial Intelligence is showing to be one of the most impactful tech trends transforming modern project management. Systematic reviews show how useful AI has been in various fields, including forecasting, scheduling, risk identification, resource allocation, classification, optimization, stakeholder analysis, knowledge management, and natural-language treating (Bachari et al., 2025; Nenni et al., 2025; Taboada et al., 2023). These applications combine to increase the analytical capacity of the project organisations, by allowing more volumes of information of diverse nature, to be handled in a faster time, and by revealing patterns that could be less easily discerned by traditional managerial analysis.

But this contribution goes beyond task automation and has been suggested by the literature increasingly. Nenni et al (2025) show that AI can transform project management processes by providing better forecasting, planning and resource allocation capabilities; Taboada et al (2023) identify AI applications during various stages of the project lifecycle. Bachari et al. (2025) also charts the development variety of project-management applications that integrate AI capabilities. In terms of knowledge, Almeida et al. (2025) see AI tools as a means of creating, storing, retrieving, and sharing project knowledge. AI can thus be seen to be less technology for efficiency, and more a new organizational intelligence infrastructure that is suspended to change the way project information is created and used. This is further complicated by the beginning of Generative AI. Generative systems engage directly with managerial cognition via conversational interfaces, document generation, information synthesis, scenario generation, and decision support, all activities that are primary functions, rather than a means to prediction and

optimization as done in earlier analytical applications. Felicetti et al. (2024) demonstrate that project managers are already using generative chatbots to do things like communications and documentation. The uses of such applications can potentially free up cognitive and administrative weights to focus managerial resources on more in-depth strategic and interpersonal responsibilities.

But technological capability does not equal organizational value. One of the captain shortcomings in abundance in the literature on AI and project management is techno-determinism: the implicit conviction that the more advanced the AI, the more likely the development will be a great success. Such an assumption may have a relatively low empirical ground. There is still a lot of systematic reviews, conceptual models and taxonomies, expert views, and studies on the application and use of AI, instead of behavioral models that elucidate the mechanisms involved in the transformation of AI capabilities into project performance (Bachari et al., 2025; Hughes et al., 2025; Nenni et al., 2025).

Empirical evidence emerging, however, indicates the contrary, a more contingent relationship. However, Alhammadi (2025) shows that the impacts of technological innovation on project-management performance happen partly by organizational level mechanisms such as sustainability culture and top-management support. Theoretically, this is major as it moves the analysis from technology to the organizational mechanisms of technology's conversion. This is clarified as AI being a valuable tool, and its actual effective use is contingent on the way project organizations: Interpret, govern, integrate and direct that tool.
Further evidence against the use of substitution to interpret AI comes from the overlap between computational ability and managerial judgment. Outside the boundary between substitution and interpretation is evidence from the overlap between computation ability and managerial judgment. When decisions need contextual interpretation and judgment, human managers still have a comparative advantage, as Barcaui and Monat (2023) show, generative AI can generate high-quality outputs for envision planning. Also, adopting generative AI does not automatically entail a smart integration of the AI into project governance, as Felicetti et al. (2024) say. An organisation could thus show high levels of AI in their day-to-day operations and be immature in AI-enabled decision making. This can be viewed as an appropriation–assimilation gap between access–use and systematic integration of AI into responsible decision processes.

Explainability supports this reason. When stakeholders and managers can no longer understand, challenge or justify the underlying logic of any AI generated recommendation, it will have limited impact in making decisions about a project that may have noteworthy consequences over the long term. Outside of direct PM use, Ali and Alaskar (2026) discuss explainable machine learning, but their methodological evidence speaks to the wider significance of interpretability where algorithmic outputs play a role in high-stakes judgement. Explainability, in the context of project governance, is not just a technological component; it could be a way to network algorithmic intelligence to trust, accountability, and managerial legitimacy.

The evidence that is emerging then argues for progressing from an automation logic to an augmentation logic. In some cases, AI can have a significant impact when computational power complements but does not replace human decision-making. The theoretical shift serves as a basis for investigating how human-centric decision-making can be a means for AI adoption to eventually help achieve project success.

2.3 Human-Centric Decision-Making in the Age of Generative AI

AI capability in PM 5.0 is social and managerial matched by human-centric decision-making (HCDM). This study defines HCDM as a range of decision processes that argue significant human agency, context-awareness, ethics considerations, stakeholder sensitivity, explainability and accountability but also incorporate algorithmic intelligence. Thus, construction does not prohibit the importance of intuition over technology. It is rather the articulation of the intentional design of decision systems in which AI enhances the analytical capacity while it does not replace the role of humans.

This is an essential part of the 5.0 paradigm industry. Human centricity alters the focus from treating a human as an adjunct to automated systems to discussing a human as an active interpreter, supervisor, collaborator and meaning-maker in technologically augmented environments (Martini et al., 2024; Dani et al., 2026). In the context of projects, this translates to AI being able to sense patterns, predict probabilities, create alternatives, and even automate information-heavy tasks, while managers play a crucial role in understanding and applying the implications of these findings in project-specific settings, since the political, ethical, strategic, and stakeholder landscape.

This supporting interpretation is corroborated by the presented evidence. Hughes et al. (2025) see AI as a critical enabler of knowledge and innovation that will bring us closer to PM2030, yet their multi-expert perspective also suggests that human skills will endure key in the process of putting technological intelligence into practice for managerial value. Similarly, Felicetti et al. (2024) show how project managers proactively adopt generative AI as a mental and productive aid. In particular, Barcaui and Monat (2023) illustrate the restrictions of algorithmic substitution: They are able to create structured planning artifacts effectively, but it is not the same as being able to replicate the contextual judgments exhibited by development managers when dealing with uncertainty, stakeholder conflict, tacit knowledge, and ambiguous goals.

The concept of complementarity in relation to sociotechnical systems is clarified very well. The sociotechnical approach considers organizational performance because of the optimal performance of both technical and social subsystems, not as such systems separated from one another. AI is the technical subsystem for construction of computational intelligence, while HCDM is the social subsystem for evaluation, contextualization, challenge, legitimization of computational intelligence.

This also makes it clear that the use of Artificial Intelligence does not ease the need for skills in management. Curiously, the more sophisticated technology, the more important and valuable the role of human judgement may become, as managers need to make results when to use these recommendations, when to change them, whose interests to pursue, and which moral or strategic implications might not be accounted for in the computation optimization. AI literacy thus needs to be contemplated as an integral component of human judgment, not a substitute for it.

In this context, HCDM can thus not only be measured as an independent indicator of project success, but also as an endogenous organizational mechanism. The use of AI raises the amount of information and analysis that is available to project decision-makers; HCDM ensures that this information and analysis are then translated into responsible and contextually appropriate decisions. This relationship is the first anticipated transmission mechanism for PM 5.0: the analytical possibilities created by AI, where AI makes analytical possibilities possible, and governance by humans is the process of making project decisions.

2.4 Sustainability Integration as a Strategic Value-Converting Mechanism

The second complementary mechanism connects to sustainability integration (SUS). Success definitions in the traditional project approach have often been defined in terms of what is considered fast, delivered on time, within scope and quality. The existing context of project environments is much wider than this narrow performance architecture, in which projects are imagined creating value in the economy, society, and longer-term from an environmental stance. Sustainability is therefore a key concern not just in terms of the products of the outcome's projects but also in the processes by which development alternatives are assessed and managerial decisions are made.

In the scope of this study, sustainability integration is the systematic consideration of the "three P's" (economic, social, environmental) in project objectives, resource selection, project governance, project monitoring, and project success indicators. This is a way of mixing sustainability unlike doing it as a reporting thing when a decision is already made on major projects. In this study, Silvius et al. 2025 shows how sustainability integration happens because of interactions with various project roles such as managers, sponsors and teams. Sustainability is thus organizationally integrated and relational, and not just a list of compliance regulations.

AI presents valuable opportunities for developing this integration. Intelligent systems could help optimize energy use, resource use, track or monitor emissions, predict the environment, and process or analyze information regarding sustainability (Demeke, 2025; Jariwala, 2024). In sustainable construction, in particular, Mahmood and Pervaiz (2026) highlight the cooperating role of education, innovation and governance, arguing that technology itself has a meaningful impact on sustainability if united into the broader capacity of organizations. But the point here is that sustainability and AI are co-creative in nature. AI can be used for sustainability, such as the optimization of resources and the prediction and monitoring of sustainability.AI can be applied for sustainability, such as resource optimization and sustainability monitoring and prediction. On the other hand, sustainability can help to constrain the aims for which AI capabilities are abused. Optimizing the cost or duration of a project might result in an efficient solution but not a socially acceptable or environmentally sound one. When integrating sustainability, the goal function is enlarged to consider impacts beyond operations.

It is especially important to note evidence that the mechanisms used to safeguard organizational sustainability can pass on technological value. Alhammadi (2025) identifies sustainability culture as the underlying factor between technological innovation and project-management performance, whereas Mahgoub and Yu (2026) focus on the strategic role of technology, collaboration, and sustainability in realizing resilience in projects. These results indicate that sustainability should not only be viewed as an outcome dependent on technological innovation. It could also be an organizational capability that can transform technological resources into greater and more sustainable project value. The dual nature of sustainability builds the character of the integration into the proposed PM 5.0 architecture. At the same time, it is assisted by AI and directed by AI: technological intelligence can support sustainability-related decisions, and, in turn, sustainability principles will distinguish what optimizations are considered as being valuable. Therefore, SUS is modelled as an AI-driven mechanism that will then have consequences for project success, thus a second pathway by which technological uptake can find project value. The overall function of HCDM and SUS corresponds but they are not the same. How that intelligence is understood is set by the processes of HCDM, and what direction it goes in is set by the processes of SUS. The former brings agency, judgement, accountability and legitimacy; the latter brings purpose, temporal orientation and environmental-social-economic alignment. The thought of their simultaneousness leads to PM 5.0 from models in which AI use is treated as a standalone technical predictor.

2.5 Jordan as a Developing-Economy Context for PM 5.0

The importance of PM 5.0 becomes especially evident when viewed in a non-technologically advanced economy. The institutional, financial, human-capital and technological environment in which AI is adopted is heterogeneous between countries and the relationships that are being experimented in resource-rich environments may not be expected to extend to the context of developing economies. The context of Jordan is important because the country is increasingly pursuing a digital and sustainability agenda, while simultaneously facing some of the typical challenges of emerging markets.

The digital environment in Jordan is marked by unfair maturity, limited resources, skills needed and developing governance capabilities. These conditions qualify the country as a country of interest, and not just as a geographically exceptional country. In such situations, if AI is able to achieve project success in the context of humans and sustainability, then the signal further supports the case that PM 5.0 is an organizational capability architecture and not an institutional luxury that can only be afforded by technically developed economies. There is unfinished support for each of these aspects in the current evidence in Jordan; however, the aspects are not integrated. This reveals the ongoing relevance of core PM skills as Kilani et al. (2024) found that scope, time, cost, and quality management all have a significant impact on both project and organizational performance in the financial sector in Jordan. Jordan's project economy also includes the construction industry, the information and communications technology sector, telecommunications, the financial sector, and the manufacturing industry, which are experiencing various technical innovations, complexities of stakeholders and sustainability pressure. There is also a theoretical question related to resource development that is revealed from the Jordanian context. Technology adoption does not take place in an institutional “bubble”. The capabilities to implement AI effectively across organizations are manipulated by managerial skills, digital governance, digital literacy, and the challenge of balancing technological possibilities with organizational limitations. In this regard, an examination of PM 5.0 in the context of Jordan offers a chance to discover the impact of human and sustainability complements on the value generated by AI, in a context where the resources of the organizations are relative.

Jordan is therefore not to be studied as just another trial run of a model that has been created in another context. Instead, it is used as a context for study of portability of emerging PM 5.0 theory. Findings from this environment can then provide clues as to whether human-centricity and sustainability are still relevant vectors of the linkage between AI adoption and project achievements, and if so, how, outside of the unconventional economy context where most of the technology-management literature focuses.

2.6 Theoretical Anchoring: Toward an Integrated PM 5.0 Architecture

None of the theories fully account for the relationships progressed by this study. PM 5.0 is at the same time about technological capacity, human–technology interaction, organizational adaptation and multidimensional value creation. Thus, the conceptual model chains three theoretical paradigms that complement each other: the sociotechnical systems theory, the dynamic capability’s view, and the triple-bottom-line framework. They are not combined to store theory but rather they are each explanation of a separate part of the same value-creation process. In this section, AI–HCDM interface will be justified using the concept of ‘sociotechnical systems theory'. This core principle is that organizational results are the result of optimizing the two (social and technical) systems at the same time, not the maximization of one system in isolation. In this vision, the use of AI is an emerging technological functionality whereas HCDM is the social architecture that will profile and translate algorithmic intelligence, making it interpretable, interrogable, contextualizable and decidable. The theory therefore provides an explanation as to why in a project, technological sophistication alone is not assumed to produce maximum project success. Second, the dynamic capability’s view is applicable for understanding how AI resources are altered to project value. The ability to have access to AI is not necessarily a long-lasting competitive edge for an organization, since these technologies are more easily learned, imitated, or purchased today. Project organizations are unique because they can identify technological opportunities and mobilize them via managerial routes, and then to reconfigure project practices in relation to them. HCDM and sustainability integration can then be understood as organizational abilities that complement each other, in which the information arising from AI is sensed, seized, and converted to project level action. This view distracts from the discussion of AI possession to the discussion of AI orchestration.

Third, the triple-bottom-line approach offers the normative structure for sustainability integration, going beyond mere economic and/or delivery aspects to the tripartite dimension of sustainability, that is, the environmental and social aspects. It plays a special role since technological optimization itself relies on the objectives that are optimized. While AI can help increase efficiency, it does not always impact a project's overall value. The value framework of technological and managerial capabilities within the context of environmental, social and economic priorities is thus offered by SUS.

These 3 views yield an organized architecture of explanation. The concept of human complementarity for AI is conceptualized in the framework of sociotechnical systems theory, the concept of dynamic capabilities for the organizational transformation of AI resources and the concept of the triple bottom line for AI's orientation to a broader understanding of value. The three attitudes then all align to the same conclusion: the connection between AI adoption and project success must be a multifaceted one that does not fit into technology-centric or directionally “as is” categories.

The synthesis will lay the foundation for the dual-mediation model presented in the next section. The technological capacity of AI is the one at the beginning of the value creation process. Algorithmic intelligence gains contextual meaning and

legitimacy via HCDM and SUS provides the strategic pathway through which the intelligence is aligned with long-term environmental, social and economic goals. The multidimensional value outcome is a result of a successful project.
In this way, the theoretical structure of PM 5.0 may be communicated as a progression between technology adoption and capability orchestration:

AI capability → human interpretation and sustainable direction → multidimensional project values.
This approach breaks away from the thinking that the next generation of project management will be real-time, technologically difficult. Rather, its vision for PM 5.0 is a triadic capability system, in which analytical power is delivered by AI, judgement and legitimacy by humans and purpose and long-term orientation by sustainability integration. These theoretical translations are now presented as causal relations and hypotheses that can be checked.

3. Conceptual Model and Hypotheses Development

Based on the theoretical synthesis in the foregoing section, this study constructs Project Management 5.0 (PM 5.0), which is a triadic capability architecture in which project success is maintained directly and indirectly by adopting AI, HCDM, and SUS. The model thus moves away from the technology-deterministic vision of AI as an independent performance driver. Rather, it takes the bearing that the value of AI relies, in part, on the organizational arrangement by which computational intelligence can be interpreted, controlled, and steered towards other project goals (see Fig. 1).

The framework proposed brings together three corresponding theoretical values. The sociotechnical systems theory is used to understand how the technical capacities that AI creates must be harmonizing with a human decision system to create project-level value; the dynamic capabilities perspective explains how the AI-related technology resources are converted into value at the development level by complementary organizational resources; and the triple-bottom-line framework elucidates why the measurement of value creation should not be limited to delivery efficiency but should include the environmental, social, and economic aspects. This conceptual model is shown in Fig. 1.

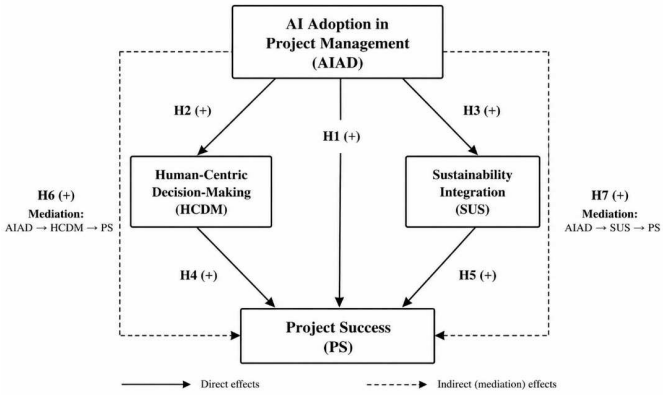

Fig. 1. Conceptual model of PM 5.0 integration.

3.1 AI Adoption and Project Success

As AI spreads its influence in project management, it is now manipulating the way we handle information and tasks.AI technology is transforming the information and operational countryside of project management as it spreads its impact in the professional field. Modern AI tools can be used to forecast better, automate repetitive tasks, facilitate schedule planning, identify potential future risks, optimize resource allocation, and streamline the generation of comprehensive project information than traditional methods (Nenni et al., 2025; Taboada et al., 2023). More generally, systematic evidence also suggests the integration of AI technologies in various phases of the project lifecycle, ranging from planning and control to knowledge management, communication, and stakeholder coordination (Bachari et al., 2025).

AI increases the ability of the project organization to sense, identify deviations, process and respond to new conditions quickly, and deal with doubt. Such capabilities play a pivotal role in project environments that are time-pressured, interdependent, information-asymmetric, and have evolving stakeholder demands. AI can augment decision latency and project team's aptitude to expect instead of just reacting to performance issues by improving the speed and quality of information processing.

This potential is expanded with Generative AI. Felicetti et al. (2024) demonstrate that Generative tools are widely utilized by development managers in tasks such as documentation and communication; Almeida et al. (2025) conceptualize the role of AI as growingly linked with project knowledge creation and transfer as an important infrastructure. Applications can help to

streamline administration, enhance access to project information and free up managerial resources to focus on more strategic activities.

Empirical studies also suggest that technological innovation can better project-management practices, but its usefulness might be linked with other complementary factors in the organization (Alhammadi, 2025). Thus, the present study does not assume that AI is a necessary condition for project success. However, its ability to increase prediction, coordination, information processing, and resources allocation seems to indicate a positive direct correlation with the outcome of projects.

H_1: *AI adoption is positively associated with project success.*

3.2 AI Adoption and Human-Centric Decision-Making

AI's increasing analytical power doesn't mean that human decision-makers are reduced and obsolete. Increasingly, AI's analytical capacity can complement and augment that of human decision-makers. On the other hand, AI can be used to cooperate with human decision-making by making information more accurate, comprehensive, and timely, providing a better basis for managerial judgment. AI-powered systems can detect patterns, create alternate solutions, summarize comprehensive data, and lighten the intellectual load when tackling repetitive analytical tasks. These capabilities can foster these capacities when the algorithmic output is interpretable and subject to the right kind of control. The argument is affiliated with the sociotechnical perspective that both technological and human capabilities must be synergized and not optimized in disagreement to each other. While AI offers analytical insights and computational power, project managers bring in contextual knowledge and tacit expertise, ethical judgment, and an understanding of stakeholder interests. What this means is that the addition of the technical subsystem is part of its value because the outputs of the technical subsystem need to be explained and contextualized by the social subsystem.

Barcaui and Monat (2023) offer valuable examples of such complementarity. Their analysis of generative AI versus project managers shows how AI can manufacture a wide range of "generative" planning artifacts, while human project managers offer value in situations where judgment calls are made in ambiguous and contextual situations. Similarly, Hughes et al. (2025) locate the capabilities of humans at the heart of the use of AI in project management, especially regarding knowledge creation, innovation, and managerial orchestration. Driven by the code of explainability this relationship once more is reinforced. Recommendations that are generated by AI will be more likely to help people to be part of a process of human-centered decision making if they can understand AI's logic, question it, and rationalize it to themselves. The remarkable findings of the explainable-AI (xAI) literature underline the significance of interpretability in boosting trust in AI-generated results and their utility for informed decision-making. Research on explainable-AI (xAI) underscores the value of interpretability in enhancing trust in AI-generated understandings and their application in meaningful decision-making (Ali & Alaskar, 2026). But the appropriate design of AI adoption does not mean it will be a replacement for human judgment; rather it may create an informational environment in which more thoughtful and responsible human judgement would be feasible. Therefore, there is likely to be a confirmed correlation between AI use and HCDM, as improved intelligence capabilities derived from AI can help supplement human agency if the AI systems are part of a responsible governance framework.

H_2: *AI adoption is positively associated with human-centric decision-making.*

3.3 AI Adoption and Sustainability Integration

AI can also reinforce the incorporation of sustainability principles into the plan decision-making process. Managers must consider more information about resource use, pollutants, environmental effects, social aspects, long-term consequences, and various stakeholder demand for sustainability-focused projects. Present decision systems might find it difficult to consistently process these heterogeneous data streams, especially in complex and dynamic project environments. AI can help solve part of this by providing advanced environmental monitoring, resource optimization, scenario analysis, waste detection, predictive maintenance, emissions assessment, and sustainability reporting. The potential role of AI in the project practices associated with sustainability is mentioned by Jariwala (2024); opportunities for interweaving AI with sustainability processes and barriers involving governance issues, skills, and data quality are summarized by Demeke (2025). All these studies show that AI can submit the analytical toolkit to integrate sustainability more systematically into project planning and control.

Alternatively, from a dynamic capabilities point of view, AI can enhance the organization's capacity to sense sustainability-related risks and opportunities and then reconfigure the endeavor activities accordingly. For instance, real-time data can help project managers recognize inept use of resources, investigate different scenarios or track environmental deviations early. In this concern, AI boosts not just operational efficiency, but also the ability to include longer-term factors in project considerations. In addition, Mahgoub and Yu (2026) stress the need to guarantee that technology, collaboration and sustainability are strategically linked to enhance resilience and performance. The argument also implies that the power of AI in analysis becomes even more significant when it's used in support of specific aims on sustainability goals and not just limited to cost or schedule optimization. Therefore, greater AI usage should support more efficient integration of environmental, social and economic aspects into development governance.

H3: *AI adoption is positively associated with sustainability integration.*

3.4 Human-Centric Decision-Making and Project Success

Increasingly successful projects trust in the quality of decisions made under conditions where there is no total algorithmic optimization. Projects are characterized by the involvement of many stakeholders, competing goals, political issues, ethical decisions, uncertainty over information and context specific restrictions. Human-centric decision making is therefore hoped to further the success of the project by keeping the interpretive and relational ability needed to handle these circumstances. HCDM builds on rational decision making with human agency, ethical responsibility and stakeholder sensitivity as well as interpretation in context. These are remarkably relevant when AI-generated recommendations seem technically best but run contrary to the expectations of stakeholders, values of the organisation or broader social factors. As described by Barcaui and Monat (2023), AI can be effective at generating project-planning outputs that are structured but is less effective at tasks that imply contextual judgement. Similarly, Martini et al. (2024) highlights the importance of human-centricity to be considered in developing AI-enhanced systems if technological sophistication is to be affiliated with human and societal goals. In a sociotechnical view, project performance will be better when the human and technology subsystems support each other instead of hindering each other. Human-centric decision processes enable project managers to appropriately assess the AI output, take tacit knowledge into account, consider concerns of stakeholders, and make decisions that could have a result. The mechanisms can reinforce trust, legitimacy and commitment and implementation quality, which purely technical models may not pay enough attention to. Hughes et al. (2025) also imagine that the future of project management will rely on the ability to integrate AI-driven knowledge with human creativity and project management capability. In the context of PM 5.0, HCDM therefore serves as a link between analytical intelligence and technically educated yet contextually legitimate and organizationally actionable decisions.

H4: *Human-centric decision-making is positively associated with project success.*

3.5 Sustainability Integration and Project Success

Project environments are increasingly complicated, and the characterization of project success has gone beyond meeting time, cost and scope requirements along with quality objectives. In an era of intensified demands by the “modern” stakeholders, projects are required to supply long-term economic return and to deal with environmental and social impacts. Therefore, the integration of sustainability should result in a positive contribution to project success, expanding the focus of managers from transporting short-term results to maximizing project values, resilience, stakeholder legitimacy and risk reduction. Sustainability integrated into projects step-by-step could be more possible to recognize and address environmental risks, deal with resource limitations, meet regulatory requirements, and better connect with stakeholders and enhance the organizational image. Silvius et al. (2025) highlights the importance of interactions between project roles and between project governance actors to achieve sustainability integration, showing that sustainability is not controlled by post-project reporting but is in fact part of managerial processes. The strategic incorporation of sustainability by Mahgoub and Yu (2026) is also linked to resilience and overall organizational performance. Mahmood and Pervaiz (2026) signify that sustainable construction, governance, education and innovation are crucial factors to succeed in more sustainable project outcomes. All the results point to the conclusion that sustainability is a driver of success not only because of its impact on environmental performance but also because of its contribution to broadening the governance framework in terms of which value is created and maintained through projects. This is of specific importance for consumption when judging the empirical findings of Alhammadi (2025) who demonstrates that sustainability culture is discovered to be a mediator between technological innovation and project-management performance. This suggests sustainability-related organizational mechanisms may be actively able to translate technological capability into performance advantages. Therefore, sustainability integration can be projected to make a positive contribution to the multidimensional project success.

H5: *Sustainability integration is positively associated with project success.*

3.6 The Mediating Role of Human-Centric Decision-Making

The hypotheses suggest that the adoption of AI is likely to affect both HCDM and project success, and that HCDM will in turn improve project victory. Together, these relationships suggest a previously undefined indirect pathway, whereby some of the impact of AI on project performance might be mediated by human-centric decisions. Theoretically based on sociotechnical systems theory, this mediation. Analytical capability is created by AI, but analytical capability is useful when it is used significantly in organizational decision-making processes. HCDM does this by enabling project managers to question, interpret, contextualize, and give legitimacy to the information generated by AI before it turns into action. As a substitute of positing a technology–performance relationship, the mediation logic also acknowledges that technological resources can affect performance via the quality of the human decision architecture that is present. This argument is established by the dynamic-capabilities approach. Organizations will have informational/analytical resources but will need complementary resources to harness these resources effectively using AI. HCDM represents such a capability, since it allows managers to mix algorithmic

information and tacit knowledge, environmental contextual information, stakeholder priorities, and ethical judgement. Therefore, the value of AI should be achieved in part by better human-decision making. The mediation the parties expect is additive and not surrogate. Beyond the tangible benefits it can provide by enhancing automation, forecasts, scheduling and resource optimization, AI can also generate indirect value by creating an environment where managers can make better decisions. Therefore, for PM 5.0, the augmentation logic implies that the impact of adopting AI has a significant human component that is also passed through to the project's success.

H_6: *Human-centric decision-making mediates the relationship between AI adoption and project success.*

3.7 The Mediating Role of Sustainability Integration

The other indirect pathway is anticipated with sustainability integration. AI can approach analytical tools needed to assess environmental and social impacts, to help optimize consumption of resources, to track sustainability indicators over time, and to reflect longer-term project alternatives. But if these capabilities are given only a 'side dish' in the definition of project objectives and project governance, they are not part of project value. The dynamic-capabilities approach proposes that organizations are not just those that own technologies, but those that are successful in using technological resources to realise strategic goals. One such mechanism of value conversion is SUS. The availability and quality of sustainability related intelligence can be enhanced by AI, whereas the integration of sustainability transforms this acumen into project priorities, trade-offs, governance practices, and/or into performance criteria. The triple-bottom-line framework also assists in making clear why this mechanism should impact on the success of the project. Technological optimization should not be only about getting things done quickly if it means only ticking off the economic, environmental or social value. When AI is combined into sustainability, the goals used to measure the impact of an AI-driven decision increase beyond cost or schedule.

There is some remaining evidence that supports this indirect argument. Alhammadi (2025) shows that culture of sustainability can act as a mediator between innovation technology and project-management performance, and Mahgoub and Yu (2026) believe that technology and sustainability must be united in a broader strategic context. In addition, Jariwala (2024) and Demeke (2025) state that AI can support some of the practices required for sustainability projects, with benefits being dependent on governance and organizational ability. The model, therefore, suggests that part of the effect of AI adoption on project success is the fact that it sponsors better integration of sustainability. Like in HCDM, direct operational benefits are likely expected to be achieved from the mediation, as well as value for the mission from sustainability-oriented governance.

H_7: *Sustainability integration mediates the relationship between AI adoption and project success.*

4. Methodology

4.1 Research Design, Population, and Sampling

The concept of the Project Management 5.0 framework was confirmed for the first time, along with the direct and indirect relationships between the elements of artificial intelligence adoption (AIAD), human-centric decision-making (HCDM), sustainability integration (SUS), and project success (PS), using this study's quantitative, deductive, cross-sectional research design. It was believed suitable to adopt a survey-based design, as the focal constructs reflected practices, perceptions and processes of management of the decisions made in an organization and with respect to its activities in project situations, which can best be taken from the professionals who are active within these situations.

The aim population included project professionals in Jordan such as project managers, project coordinators, project management office (PMO) staff members, and senior managers or sponsors who are directly involved in project-related decision making. To boost contextual and sectoral diversity, respondents were nominated from four project intensive sectors: construction and engineering, information technology and telecommunications, banking and finance, and manufacturing. The major economic centers in Jordan, such as Aqaba, Irbid, Zarqa and Amman were the area where data was collected. The target of this multi-sector design was to minimize reliance on the practices of a single sector, and to offer a wider test of the proposed PM 5.0 relationships.

Since there was no national sampling frame to identify all the project professionals in these sectors, the study used stratified convenience sampling. Sectoral stratification was working to ensure representation from the key sectors included in the research and convenience-based access was utilized to guarantee eligible project professionals participated. It does not represent probability sampling, but having respondents from various professional roles, sectors and geographical areas adds to the section heterogeneity and emphasizes the relevance of the empirical analysis being used.
Information was assumed to use online and field-administered questionnaires from March to May 2026. 500 questionnaires were sent out and 412 were returned. After data screening for usability and completeness, 384 questionnaires were retained and an effective response rate of 76.8% was obtained. The final sample of respondents, however, were only those who had concluded questionnaires containing adequate information for later statistical analysis.

The adequacy of the samples was checked before the estimation of the structural models. The anticipated effect size ($f^2 = 0.15$) was used with a level of significance ($\alpha = 0.05$) and statistical power ($1 - \beta = 0.95$) for an a priori statistical-power assessment, based on the G*Power software. The requisite came out to be comfortably lower than the achieved sample of respondents, which was 384. The sample was also larger than traditional minimum heuristics in previous PLS-SEM studies. More important, yet sample size was calculated not only according to the 10-times rule as it is recognized that it is a guide relying only on the minimum sample size, but also on a statistical-power analysis. The obtained sample size was acceptable to estimate the proposed structural relationships and two parallel mediation mechanisms and remained meaningful across various sectors of the project environment in Jordan.

4.2 Measurement Development and Instrument Design

Four latent factors: AI adoption (AIAD), human-centric decision making (HCDM), sustainability integration (SUS), and project success (PS) were operationalized using the questionnaire. Items for measuring AI-enabled management, human-centered decision processes, sustainability-oriented project practices and multidimensional project performance were adapted from existing endorsed conceptualizations and empirical scales. There was a need to adapt the proposed model, rather than simply replicate it, because the proposed model is a mix of constructs that have typically been studied individually and not in the context of an amalgamated PM 5.0 model.

Each of the construct items was rated on a 5-point Likert-type scale from 1 = strongly disagree to 5 = strongly agree. A respondent burden reduction and across form consistency was employed through a consistent response format. Four indicators were used to operate the use of AI: capture the use of AI-enabled technologies in core managerial activities related to the project. Indicators focused on leveraging predictive analytics, automation, machine-learning based risk tools, and generative-AI applications. This operationalization demonstrates the way in which the study accepted an approach to the use of AI as an organizational project capability instead of simply technology made available.

The extent to which AI supported project decisions did not eradicate human oversight, allow human ethics, build stakeholder empathy in the decision-making process, and actively seek explainability, along with other indicators, were captured as a measure of human-centric decision-making. The indicators are informed by the PM 5.0 central proposition that artificial intelligence should be used to balance instead of replacing human judgment. Accordingly, HCDM is not just about managerial engagement, but also how decision authority, contextual interpretation, and accountability are still meaningfully absorbed into AI-assisted processes.

Four indicators echoing the inclusion of environmental, social, and economic aspects of sustainability in project-management practices as well as sustainability monitoring or green monitoring were used to measure sustainability integration. The structure thus represents the level of integration of sustainability issues in the decision-making about the project, in its governance, and in its management, not just as a peripheral reporting obligation. Project success was defined in terms of four indicators that go elsewhere than the conventional iron-triangle criteria. What was captured were objective project performance, satisfaction of stakeholders, strategic benefits and sustainable outcomes. This is more of an operationalization of the theoretical foundations stated in PM 5.0 that today's projects can't be glanced at only through time, cost and scope performance.

Prior to the full-scale data collection, the content validity and the contextual appropriateness were assessed. A panel of 5 experts – 3 academics and 2 experienced practitioners – reviewed the initial questionnaire. The panel assessed the precision of items, conceptual consistency, terminology and appropriateness for the Jordanian project-management setting. They supplied some language changes that led to a few refinements in the wording of the constructs but didn't change the conceptual content themselves. The new instrument was then pilot tested with 40 participants from the target professional population. The pilot exercise was employed to see how understandable the questions were, how much effort it would require working through the questionnaire, and whether there were any misunderstandings. Minor wording was needed and after these changes it was finalized for the main data collection phase. The chain of literature-based item modification, input from experts, and pilot testing enhanced the content validity and scope for use of the measurement tool.

4.3 Procedural Controls, Ethical Considerations, and Common-Method Bias

All focal constructs were assessed using a single survey measure, which is why CMB was a specific concern of the research design. In addition to using only statistical diagnostics of the process at the end, sequential use of both procedural and statistical controls was used.

The procedure was integrated to inform respondents that participation was voluntary, and any information they provided would not be identifiable. There was no personally identifying data to be included in the analytical dataset. In addition, participants were told about the study and gave their learnt consent. Ethical approval for the main data collection stage was granted by an institutional review body at a Jordanian university before the study.The institutional ethical board of a Jordanian university arranged our study prior to the main data collection stage.

The questionnaire was designed with a further attempt to minimize evaluation apprehension and consistency motives. During the development of the questionnaire, predictor and criterion constructs were presented psychologically as detached, and not as an apparent causal sequence. Responses were phrased in a neutral manner to reduce socially desirable responding, therefore there were no right or wrong answers, nor were there preferred answers. Statistically common-methods were then tested. The first was Harman's one factor test which was carried out in IBM SPSS Statistics 29. First unrotated factor's percentage of the total variance was 36.42%, which was lower than the generally accepted 50% rule. Harman's test alone is not appropriate to rule out common method variance, but the result didn't suggest that there was one dominant factor affecting the covariance among the observed variables. To be able to discover the second diagnostic, the Full collinearity variance inflation factor approach was therefore applied in the software program SmartPLS 4. Additional evidence of no likely dominance of the estimated relationships due to pathological collinearity or a significant common-method variance was provided by the fact that no full-collinearity VIF values were above 3.3. Viewed together with the procedural precautions which were built into the development of the survey, these diagnostics indicated that common-method bias was not likely to pose a serious problem or question to the interpretation of the structural results found.

4.4 Data Screening and Preliminary Analysis

The data passed through a preliminary screening before assessing the measurement and structural models using IBM SPSS Statistics 29. The research of this stage was oriented towards the preparation and examination of data for multivariate analysis and the empirical structure of the measurement instrument.

First descriptive statistics were calculated to portray the sample and to check the distributions of the variables observed. The measurement items were then subjected to exploratory factor analysis (EFA) as an initial exploratory examination of the dimensional structure of the items. The Kaiser–Meyer–Olken (KMO) test of sampling adequacy was 0.912, which is high, pointing that the correlation matrix is very appropriate for factor analysis. A test for sphericity performed by Bartlett was statistically significant ($p < 0.001$) and the null hypothesis that the item correlation matrix is an identity matrix was denied.

The solution found through exploration analysis gave rise to four factors that accounted for 68.74% of the total variance, which were the four constructs that were theoretically detailed: AIAD, HCDM, SUS, and PS. The EFA was used to preliminarily diagnose the measurement model for the ensuing stage of measurement-model analysis in PLS-SEM to avoid using it as a substitute for the measurement-model analysis in PLS-SEM. Reliability, the convergent and discriminant validity were thus assessed individually in SmartPLS 4 before any conclusions on structural relationships were drawn. This two-step process allowed us to discriminate between the initial examination of the item structure and the theory-based evaluation of the measurement model to diminish possible prematurely drawn conclusions about the structure before achieving a sufficient level of measurement quality.

4.5 PLS-SEM Estimation Strategy

The hypothesized relationships were estimated using partial least squares structural equation modelling (PLS-SEM) in SmartPLS 4. PLS-SEM was chosen because the study aims to simultaneously evaluate a multi-construct explanatory model, estimate parallel mediation mechanisms and investigate the predictive relevance of the endogenous constructs. The method is especially suitable for research that involves both theory development and theory explanation that stresses variance accounted for of key outcomes (refer to Fig. 2).

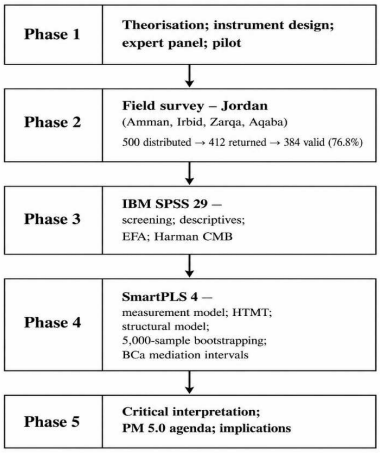

Fig. 2. Two-stage analytical workflow (SPSS 29 + SmartPLS 4).

Structural equation modelling sequence of analysis was understood as recommended for variance-based structural equation modelling. The measurement model was judged first to make sure that the underlying constructs were sufficiently reliable and valid to interpret the assumed structural paths. Outer loadings were used to test indicator reliability and Cronbach's alpha and composite reliability to test internal consistency. The average variance extracted (AVE) was used to evaluate convergent validity, and the heterotrait–monotrait ratio (HTMT) and complementary construct-level diagnostics were used to assess discriminant validity. After establishing good measurement properties, the structural model was estimated with the following parameters: path coefficients, collinearity diagnostics, explanatory power, effect size, predictive relevance, and model-fit parameters. R^2 was used to assess the descriptive power of the model, and f^2 was used to measure the incremental effect size of each exogenous construct. In addition to sample explanatory assessment in a form of Q^2, predictive relevance was also assessed. The statistical significance was settled using bootstrapping with 5,000 resampling. Reliability of the modeled direct and indirect effects was assessed using bias-corrected confidence intervals. Bootstrapping also played an important role in the mediation analysis because testing distributions of indirect effects are generally not normally distributed.

4.6 Mediation Testing

The foundational theoretical comprehension of the model is that HCDM and SUS are two parallel transmission mechanisms between the use of AI in projects and project success. The mediation test was tested directly by estimating the specific indirect effects: AIAD → HCDM → PS and AIAD → SUS → PS.

An indirect effect was deemed to have substantial evidence if the 95% bootstrapped confidence interval was not empty. The interpretation of mediation was applied to the direct effect of AIAD on PS plus each mediation path for the specific indirect effects, not just to the path that is statistically significant. This allows for qualifications of direct-only, indirect-only, complementary and even competing forms of mediation. The suggested theoretical model would imply that when the direct impact of AI on project success is still strong, and there are still sturdy indirect impacts on project success via HCDM and SUS, complementary mediation will take place. Theoretically this is allied with the PM 5.0 proposition on project value added by AI and its complementary human-centered and sustainability-based mechanisms. Therefore, the conciliation analysis is a more robust test of the theoretical argument of the study than a direct-effects model. While simply judging the achievement of AI adoption is popular, creating a capability from AI and transforming it into project value can be assessed as well.

4.7 Integrated Analytical Protocol

The overall analytical approach was thus sequential and used two software. Data screening, descriptive analysis, exploratory factor analysis and the preliminary common-method-bias (CMB) diagnosis were handled using IBM SPSS Statistics 29 software. The validation of measurement model, estimation of structural model, the assessment of prediction, bootstrapping and mediation analysis were then overseen using SmartPLS 4.

The Workflow was as follows:

Data collection, Preliminary descriptive analysis & factor analysis, Common-method-bias assessment, Measurement-model evaluation, Structural-model evaluation, Predictive evaluation, Direct-effect test and Indirect-consequence test, Mediation interpretation. Each statistical technique wrought a very specific methodological function, and structural inferences were made only after determining the validity of the measurement model.

5. Results

5.1 Sample Profile

The characteristics of the respondents in terms of their demography and profession are summarized in a tabular form in table 2. Most of the sample was male (61.5%) with women accounting for 38.5%. According to age, the highest percentage mentioned was the 30-39 age range (43.8%) followed by the 40-49 age range (25.5%). Individuals from mid-careers tended to make up many of the project professionals.

The level of education received was relatively high. Most respondents (55.2%) had a bachelor's degree, 36.7% had a master's and 8.1% had doctorate. Other sections were also varied in terms of the relative proportion of the sample, with construction and engineering coming in at 30.7%, IT and telecoms at 24.0%, banking and finance at 18.5%, manufacturing at 15.1% and consulting and other project-related activities at 11.7%.

The same applies to the professional experience distribution, with the respondents: About 37.0% said that they had 5 to 10 years of project management experience and 38.0% had more than 10 years of project management experience. Formal certification, 33.3% said they were PMP certified and 20.8% said they had another recognised qualification like PRINCE2. The numbers were not all sunny, however, 45.8% of respondents were not formally project managed. The sample provides a diverse mix of experienced and educated project personnel from a range of sectors on a project basis. Concurrently, the

comparatively high share of non-certified professionals indicates that AI-supported project management has a degree of uneven formalization on the way to professionalization. However, the comparatively high share of non-certified professionals also must be interpreted in the light of the skill requirements of AI-supported project management, because of the uneven formalization on the way to professionalization.

Table 1
Demographic and professional profile of respondents (n = 384)

Characteristic	Category	n	%
Gender	Male	236	61.5
	Female	148	38.5
Age	< 30	74	19.3
	30–39	168	43.8
	40–49	98	25.5
	≥ 50	44	11.5
Education	Bachelor	212	55.2
	Master	141	36.7
	PhD	31	8.1
Sector	Construction/Engineering	118	30.7
	IT & Telecommunications	92	24.0
	Banking & Finance	71	18.5
	Manufacturing	58	15.1
	Other/Consulting	45	11.7
PM experience	< 5 years	96	25.0
	5–10 years	142	37.0
	11–15 years	89	23.2
	> 15 years	57	14.8
Certification	PMP	128	33.3
	PRINCE2/Other	80	20.8
	None	176	45.8

5.2 Measurement Model Assessment

Before examining the hypothesized structural relationships, it was chosen to test the measurement model. The outer loadings were first analyzed to determine indicator reliability. All the indicator loadings for the items were above the 0.70 threshold, with values ranging from 0.744 to 0.873, which fell under the satisfactory range of item reliability. Cronbach's alpha was applied, as well as composite reliability, to check the internal consistency of the scales. Cronbach's alpha and composite reliability values gone from 0.856 to 0.893, and 0.894 to 0.918, respectively. All scores are above the normal range and show high internal consistency on each of the four constructs. Average variance extracted (AVE) was used as a measure-to-measure convergent validity. The AVE values were between 0.625 and 0.691, which is higher than the suggested AVE value of 0.50. Given this, every latent construct accounted for over 50% of the variance in its indicators, which was evidence for convergent validity.

Table 2
Reliability and convergent validity

Construct	Item	Loading	Cronbach's α	CR	AVE
AI Adoption (AIAD)	AIAD1	0.842	0.867	0.902	0.649
	AIAD2	0.817			
	AIAD3	0.794			
	AIAD4	0.768			
Human-Centric Decision-Making (HCDM)	HCDM1	0.861	0.884	0.917	0.691
	HCDM2	0.838			
	HCDM3	0.802			
	HCDM4	0.771			
Sustainability Integration (SUS)	SUS1	0.829	0.856	0.894	0.625
	SUS2	0.806			
	SUS3	0.781			
	SUS4	0.744			
Project Success (PS)	PS1	0.873	0.893	0.918	0.691
	PS2	0.851			
	PS3	0.812			
	PS4	0.786			

To evaluate the discriminant validity, the Fornell-Larcker measure as well as the heterotrait – monotrait ratio was applied. Table 3 demonstrates that the square root of the AVE of each construct was greater than the inter-construct correlation for each, as required. Additionally, all the HTMT were below 0.90. The findings suggest that though these constructs share a theoretical relationship, they can be analytically differentiated into distinct constructs, namely AIAD, HCDM, SUS and PS.

Table 3
Discriminant validity: Fornell–Larcker and HTMT

Construct	AIAD	HCDM	SUS	PS
AIAD	0.806	0.742	0.701	0.738

HCDM	0.612	0.831	0.664	0.771
SUS	0.578	0.549	0.791	0.712
PS	0.634	0.661	0.602	0.831

Note: Diagonal values represent the square roots of AVE; values below the diagonal are inter-construct correlations, and values above the diagonal are HTMT ratios.

5.3 Structural Model Assessment

The measurement model was confirmed before the evaluation of the structural model in terms of its explanatory power, its predictive relevance, the effect sizes and the statistical significance of the calculated paths. The model accounted for 37.5% of the variance in HCDM, 33.4% of the variance in SUS and 58.7% of the variance in project success. A high R^2 value of project success indicates that there is a high level of explanatory power for a behavioral model that includes technological, human and sustainability-related predictors. This was supplemented by the foretelling relevance. The Q^2 values for HCDM (0.238), SUS (0.211) and project success (0.364) were greater than zero. The SRMR value was 0.058, which again specified a good approximation of model fit, and the NFI value was 0.874. The structural-model results are shown in Table 5.

Table 5
Structural-model results and hypothesis testing

Hypothesis / Path	β	t-value	p-value	f^2	95% BCa CI	Decision
H_1: AIAD → PS	0.284	4.87	< 0.001	0.089	[0.171, 0.398]	Supported
H_2: AIAD → HCDM	0.612	12.84	< 0.001	0.602	[0.521, 0.694]	Supported
H_3: AIAD → SUS	0.578	11.47	< 0.001	0.505	[0.482, 0.667]	Supported
H_4: HCDM → PS	0.331	5.62	< 0.001	0.121	[0.217, 0.446]	Supported
H_5: SUS → PS	0.296	5.11	< 0.001	0.097	[0.184, 0.409]	Supported
H_6: AIAD → HCDM → PS	0.203	4.71	< 0.001	,	[0.124, 0.289]	Supported
H_7: AIAD → SUS → PS	0.171	4.35	< 0.001	,	[0.101, 0.247]	Supported

Model summary: R^2(HCDM) = 0.375; R^2(SUS) = 0.334; R^2(PS) = 0.587; Q^2 = 0.238, 0.211, and 0.364; SRMR = 0.058; NFI = 0.874.

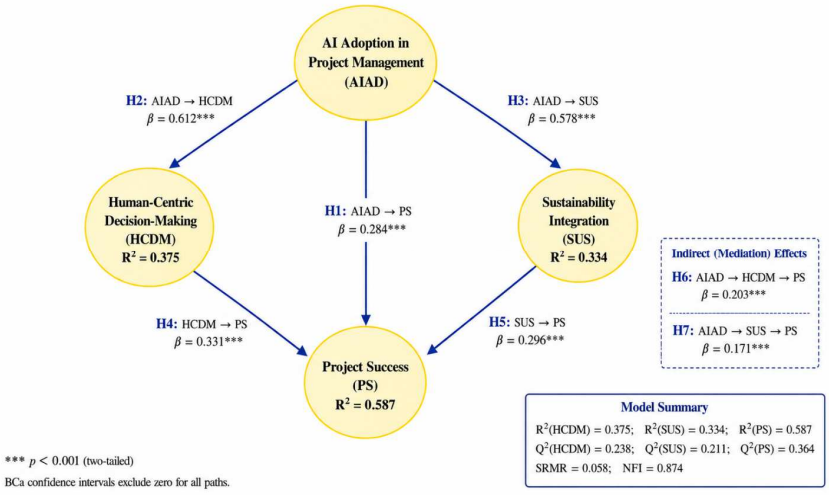

Fig. 3. Estimated PLS-SEM path model of Project Management 5.0.

Project success was also significantly directly enhanced by AI adoption, with β = 0.284, p < 0.001, which in turn was used to back up H_1. The effect size was relatively small (f^2 = 0.089), indicating that AI does have a specific role in project success, but it's not necessarily the primary driver of project value alone.

The two mediators proposed were significantly more affected using AI. It was positively related and statistically significant with HCDM (β = 0.612; p < 0.001; f^2 = 0.602) that supported H_2. Likewise, the use of AI greatly contributed to sustainability integration (β = 0.578, p < 0.001, f^2 = 0.505) for H_3. The two paths make up the highest impact in the structural model.

The mediators in turn had a positive effect on project success. The results for H_4 and H_5 indicate that HCDM had a significant positive impact on the success of the project (β = 0.331, p < 0.001) and sustainability integration also had a significant positive effect on project success (β = 0.296, p < 0.001). Combined, these direct effects indicate that the potential direct impact of AI in changing outcomes of projects might not only be on project outcomes, but on the decision and sustainability capacity that project outcomes are realized through.

5.4 Mediation Analysis

The proposed PM 5.0 architecture is tested most clearly by the mediation analysis. Specific indirect effects for both were positive and significant with 5,000 resamples. The indirect effect of AI adoption on the project success via HCDM was 0.203 ($t = 4.71$, $p < 0.001$) with a 95% bias corrected confidence interval of [0.124, 0.289]. H_6 is supported as it does not include 0. Likewise, the indirect effect mediated by sustainability integration was 0.171 ($t = 4.35$, $p < 0.001$) with a 95% confidence interval of [0.101, 0.247] which supported the H_7 hypothesis. Importantly, the direct AIAD → PS relationship was also positive and statistically significant when the mediators were added. Concomitant existence of meaningful direct and indirect effects is a commentary on the 'complementary partial mediation' phenomenon. Approximately 30.9% of the total effect related to AI was contributed by the HCDM pathway and 26.0% was contributed by the SUS pathway. These two indirect channels make up about 56.8% of AI's total link to project success. The pattern reflects that a significant portion of the value of AI adoption is shared and transmitted through the organizational processes and mechanisms used to put the technology into practice, not just by its capability.

6. Discussion

The findings corroborate the main thesis of the PM 5.0 framework: The impact of AI on project success is greatly influenced by the human and sustainability systems that it is part of. In particular, three results are significant.

6.1 AI Creates Project Value, but Its Strongest Effects Are Indirectly Organisational

The first discovery: Use of AI has a positive effect on project success. This finding aligns with previous studies that have shown the potential of AI to enhance forecasting, resource management, risk assessment, scheduling, and information handling throughout the project lifecycle (Bachari et al., 2025; Nenni et al., 2025; Taboada et al., 2023). It also corresponds with the evidence provided in Alhammadi (2025) on how technological innovation can help enhance project-management performance. But the relative size of structural relationships can be interpreted more theoretically. The coefficient of the direct path (AIAD → PS) was significantly lower than the coefficient of the direct path for AI effects on HCDM (0.612), and SUS (0.578). So, it seems, AI does much more to influence the capability set of project decision-making than it does to create project success on its own. The outcome defies the notion of AI-powered project management as technology-driven. While the embedded nature of AI can boost operational processes, the advantages associated with technological adoption cannot be quantified in this way. Instead, AI is especially impactful when it enhances the quality of the organizational processes used to make decisions and set priorities for projects.

This interpretation aligns with that of Barcaui and Monat (2023), which showed that generative AI can simulate key planning tasks, but with a lack of contextual judgment, while Felicetti et al. (2024) showed that the use of generative AI is not always strategic assimilation. This is the first study to demonstrate quantitatively that organizational impacts of AI on human-centricity and sustainability outweigh its direct impact on performance. The empirical evidence accordingly indicates support for an augmentation instead of an automation interpretation of PM 5.0.

6.2 Human-Centric Decision-Making Converts Analytical Intelligence into Legitimate Action

The second result is related to the HCDM pathway. Human-centric decision making was significantly impacted using AI, and this impacted on project success. The increased indirect effect of 0.203 is evidence that HCDM is not only an accompanying principle of Industry 5.0, but also a value conversion mechanism that can be observed in practice. This lends supporting evidence to the sociotechnical systems theory. AI is an extension of this technical subsystem, which involves quickening and widening how much information is processed about projects, and making it more sophisticated. HCDM enhances this capability by maintaining considerations of context, stakeholder sensitivity, ethical judgment and accountability. Performance, then, is not an inherent attribute of either but is a result of the interplay between the two systems – computational intelligence and human judgement.

The discovery also sheds light on conflicting reports on the influence of AI in management decisions. Currently, AI is often presented as an alternative to human analysis, especially when it comes to things like report generation, plans, scenarios, and recommendations. However, Barcaui and Monat (2023) show that creating technically competent work does not reflect a sense of judgement in the face of ambiguity. In a similar vein, human-centricity should be built into the design of systems incorporating AI, and not used as a corrective measure, as Martini et al. (2024) point out.

The present results support this argument by proving that greater the adoption of AI, the greater the influence of the human element on the decision-making process, not the lesson of it. This implies that technologically advanced project worlds don't have to diminish humans. If managed well, techno-sophication can provide the informational basis for more deliberate human judgment.

6.3 Sustainability Integration Functions as a Value-Converting Mechanism

The sustainability pathway also gives rise to a theoretical implication that is important. The use of AI dramatically contributed to achieving sustainability integration within organizational projects, thereby boosting project performance. The indirect effect of 0.171 verifies that sustainability is not only a project goal, but also a means of transforming technological capabilities into overall project benefits. Will conclude that sustainability culture is somehow in the middle between technological innovation

and project-management performance, which aligns with Alhammadi's (2025) findings. Furthermore, it aligns with the work of other researchers such as Jariwala (2024), who emphasize the contribution of AI in environmental monitoring, and Demeke (2025), who focus on resource optimization and sustainable decision-making. But the connection shouldn't be viewed as simply technological. The AI cannot identify which objectives to focus on; it can only optimize the objective of the user. The integration function of sustainability does this by expanding the scope of the optimization criterion beyond cost, schedule, and short-term operational efficiency to include environmental, social and long-term economic considerations. This is why AI and sustainability will not be viewed as siloed development. In PM 5.0, technological capability provides analytical power, and the purpose in which the capability is applied to achieve sustainability is determined.

6.4 Dual Mediation Reveals the Behavioural Architecture of PM 5.0

The key finding relates to the co-occurrence of the two mediators. The proportion of HCDM and SUS together is a significant share of the whole relationship between AI and success. They do not compete. Theoretically, each mechanism performs a different function. HCDM is a response to that question of how to interpret and legitimize an Ai enhanced intelligence; SUS is a response to the question of what conception of value that intelligence should serve. Sustainability provides direction, temporal horizon and environmental-social-economic alignment and human-centricity provides agency, judgement, ethics and stakeholder legitimacy. This separation of tasks makes a difference from models which simply try to put together several good project attributes. The results indicate that PM 5.0 should be viewed as a tritium capability system. AI gives intelligence, humans give judgement and sustainability gives direction. The success of a project isn't about maximizing any single component of it; it's about optimizing all three.

6.5 Interpreting PM 5.0 in the Jordanian Context

The relevance of the model is further supported by evidence from Jordan. Some of the previous studies in Jordan reveal that traditional project-management skills like scope, time, cost and quality management still play a significant role in success (Kilani et al., 2024). The present findings do not challenge this base; rather, the next phase of project capability would demand the integration of these known disciplines and the addition of increasingly related projects with decision systems leveraging the power of AI and project governance with a focus on sustainability.
Jordan is of theoretical importance since the PM 5.0 relationships occur in a context of relatively limited resources and different degrees of formal professionalization. Nearly 46% responded to the question that they had no formal PM certification. This indicates that the challenge of implementing PM 5.0 is not just a technology adoption problem. It also deals with human-capital development, AI literacy, professional capability and maturity governance.

Results should be generalized, however, with caution. Jordan provides evidence that the proposed capability relationships are observable in contexts other than those with high amounts of resources, but a single-country design will not prove universal applicability. The Jordanian evidence is valuable, however, in emphasizing the need to reject the perception that PM 5.0 is a technological luxury that can only be found in advanced economies.

7. Theoretical Implications

There are four major ways in which this study adds to the growing body of PM 5.0 studies. The first is the shift from the conceptual discourse of PM 5.0 to an empirical one in terms of operationalization. There is a lack of empirical models that combine the human-centric, sustainable, and technologically aided nature of Industry 5.0 project management, as existing studies have only been able to articulate this nature. Existing studies have only articulated the human-centric, sustainable, and technologically enabled character of Industry 5.0 project management, and there are limited empirical models that integrate these aspects. This framework translates the concept of AIAD, HCDM, SUS and PS into distinct but interrelated constructs in a single structural model. Second, the study adds in terms of specifying mechanisms rather than just relationships. While existing reviews show the impact that AI can have on project processes and outcomes (Bachari et al., 2025; Nenni et al., 2025; Taboada et al., 2023), little is known about the process through which technological capability gains project value. The dual-mediated findings fill this gap by identifying two human-centric decision-making and sustainability integration mechanisms.

Thirdly, the findings substantiate the integration of sociotechnical systems theory, dynamic capabilities and the triple-bottom-line framework. The complementarity between AI and human judgement is described by sociotechnical theory. Dynamic capabilities lie in the ability to transform technological resources into value in the company through complementary capabilities. The triple bottom line helps to explain the many-dimensional nature of that value. The results taken together suggest a triple facet of that value of AI: technical, behavioural, and normative, when it comes to project-management.

Fourth, the study broadens the geographical scope of the research of AI-enabled PMs by offering evidence from Jordan. Fourth, the study contributes to the geographical scope of the AI-enabled PM research; the study provides evidence from Jordan. The results indicate that similar capability mechanisms can also be implemented under conditions of a higher level of resource constraint if emerging PM 5.0 relationships can be limited to technologically advanced environments.

There is a theoretical implication here that isn't as narrow as the individual hypotheses: The impact of adoption of AI should not be seen as a stand-alone factor of project performance, but as a contributing variable to an organizational capability system.

8. Practical and Policy Implications

The findings also offer a clear implication for management: Don't think of AI investment as a digital-transformation program. The comparatively robust AIAD and AIAD-HCDM and AIAD-SUS connections indicate that the returns to AI may rely on whether complementary governance and sustainability capacities are co-developed or not. Project-management offices must institute human-in-the-loop decision processes for relevant decisions made with AI assistance. Project managers should not just follow algorithmic advice, but question assumptions, evaluate the context, think about the impact of stakeholders and record accountability for decisions that are not in line with algorithmic advice. The same decision-making structure should also be used to incorporate sustainability metrics. Information systems and dashboards should thus track not only the resources consumed, environmental effects, stakeholders' impacts, and project values in the long term, but also cost, time, scope, and quality. It is also vital that capability is developed. AI literacy, algorithmic output critical interpretation, ethics, stakeholder management, and sustainability assessment are all important aspects which should be included in the training programmers, not as standalone skills. The strategy directly addresses the gap in appropriation–assimilation gap previously seen in the previous generative-AI research (Felicetti et al., 2024). The findings offer implications for Jordanian policymakers and professional organizations for developing digital-transformation strategies in tandem with investments in professional capability. Increased access to project-management certification, AI-related professional education, and sustainability reporting skills, as well as responsible-AI governance, could help improve institutional factors that facilitate the adoption of PM 5.0. Policy implications, therefore, are not just about the uptake of more AI by organizations. It is to spur them to build human resource and sustainability structures needed to properly steward AI products.

9. Limitations and Future Research

There are some caveats. First, there are limitations in making causal inferences in a cross-sectional design. The hypothetical relationships are theoretically based but cannot definitively be determined by a one-wave survey. Longitudinal studies could investigate the correlation between the use of AI and subsequent development of HCDM and sustainability skills and the resulting impact on project outcomes.

Secondly, the study uses self-report measures of perception. Future research should add perceptual data, digital-system telemetry, sustainability data, and project KPIs to the list of metrics used to measure AI usage.

Third, the method of sampling naturally selected a convenience sample, which limits the ability of generalising results. Future replications could benefit from probability-based sampling or access to national professional records.

Fourth, the single country design establishes an important boundary condition. Comparative studies between economies in Jordan, across the countries of the Gulf Cooperation Council and within the MENA region could explore the moderating effect of institutional quality, digital maturity, organisational culture, or institutional environments on the proposed relationships.
Future research ought to investigate sector-level heterogeneity, fifth. There are some differences in the value of AI-backed HCDM between the construction, IT, finance, manufacturing, public infrastructure, and megaprojects environments.

Methodological architecture could be extended in future work. Longitudinal PLS-SEM or covariance-based SEM might test the extensions over time and confirm the extensions, whereas the extensions of equifinal combinations of AI, human-centricity, sustainability, leadership and governance to produce high project success could be investigated using fsQCA. Multi-group analysis might identify differences in relationships between sectors, certification levels, experience types and marks the various levels of AI maturity.

Last but by no means least, generative AI needs more explicit consideration as a team- and governance-level phenomenon. Conversational AI is becoming more integral to the daily project workflow and further investigation is warranted into explainability, accountability, trust calibration, automation bias, and the shift in decision making power in the project team.

10. Conclusion

As the switch from Industry 4.0 to Industry 5.0 approaches, it is essential to shift the perception of the added value of AI in project management. Rather than just asking if AI can enhance forecasting, scheduling, risk analysis, and resource allocation, the central question now revolves around how these tools can be integrated into organizational frameworks that ensure that while technology provides insights, human judgment remains at the core. Instead of only asking if AI can help with forecasting, scheduling, risk analysis, or resource allocation, the question now is how these capabilities can fit into organizational systems with sustainable value creation, with the human eye holding the steering wheel and directing technological intelligence.

An empirical approach to answering this question is proposed using the PM 5.0 model. The findings suggest that although the extent of the impact of AI on project success is positive, much of the link is mediated by human-centric decision making and sustainability integration. AI as a standalone solution to managerial skills does not seem to offer the greatest value, instead as part of a holistic organizational structure.

This discovery takes a new look at PM 5.0 as a triadic capability system. The elements of AI are analytical intelligence, human-centric decision-making is contextual judgement, accountability and legitimacy and sustainability integration is direction and long-term value orientation. Successful projects are not necessarily technologically advanced – they are a product of the coordination of these capabilities.

From theory, this will move the discussion of AI–PM up a gear from adoption to value-conversion mechanisms. It means that investing in AI also requires investing in human judgement, explaining AI, responsible governance, and sustainability capability for the practitioners. It also argues that building professional and institutional capacity is as important as deploying advanced technologies to move developed economies toward PM 5.0 as it is in developing economies like Jordan.

Project Management 5.0 is not, therefore, dependent upon the use of artificial intelligence. It's the ability to make sure that A.I., human judgment and sustainability goals work together as one cohesive unit that results in long term project value.

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Appendices

Appendix A: Survey Instrument and Contextual Adaptation

A.1 Instrument Development and Translation Protocol To ensure construct validity within the Jordanian context, the survey instrument underwent a rigorous methodological protocol. Items were initially synthesized from seminal and recent systematic reviews (e.g., Bachari et al., 2025; Nenni et al., 2025; Silvius et al., 2025). Following established cross-cultural research guidelines, the English instrument was translated into Arabic by a bilingual academic expert in project management, and subsequently back-translated into English by an independent professional translator. Discrepancies were resolved through a panel review comprising three senior academics and two PMO directors from Amman-based enterprises. The final Arabic version was piloted with 40 project professionals to assess cognitive debriefing, ensuring that Industry 5.0 terminology (e.g., "generative AI," "circular economy principles") was interpreted consistently across the construction, IT, and financial sectors in Jordan.

Table A1
Operationalization of Latent Constructs and Measurement Items.

Construct	Code	Measurement Item (Adapted for Jordanian PM Context)	Outer Loading (λ)	t-value	Source Anchors
AI Adoption (AIAD)	AIAD1	Our project teams use AI tools for predictive analytics and risk forecasting.	0.842	18.42	Nenni et al. (2025); Taboada et al. (2023)
	AIAD2	We integrate machine learning algorithms to optimize project scheduling and resource allocation.	0.817	15.11	
	AIAD3	Generative AI applications are routinely utilized for project documentation and stakeholder communication.	0.794	12.87	Felicetti et al. (2024)
	AIAD4	AI-enabled dashboards are employed for real-time monitoring of project KPIs and cost variances.	0.768	10.54	
Human-Centric DM (HCDM)	HCDM1	Human project managers retain the final authority over AI-generated recommendations.	0.861	21.34	Martini et al. (2024)
	HCDM2	We actively ensure that AI tools provide explainable outputs before making critical decisions.	0.838	17.92	Ali & Alaskar (2026)
	HCDM3	Ethical considerations and stakeholder empathy are prioritized over purely algorithmic efficiency.	0.802	14.26	Dani et al. (2026)
	HCDM4	Project teams regularly override AI suggestions when contextual or moral nuances require it.	0.771	11.05	Barcaui & Monat (2023)
Sustainability Integration (SUS)	SUS1	Environmental impact assessments are deeply integrated into our project planning phases.	0.829	16.88	Silvius et al. (2025)
	SUS2	We utilize digital tools and AI to monitor and reduce the carbon footprint of our projects.	0.806	14.55	Jariwala (2024); Demeke (2025)
	SUS3	Project success criteria explicitly include long-term social and economic value creation.	0.781	12.19	Mahgoub & Yu (2026)
	SUS4	Circular economy principles guide our procurement and resource management decisions.	0.744	9.87	Mahmood & Pervaiz (2026)
Project Success (PS)	PS1	Our projects consistently meet or exceed their defined scope, time, and budget constraints.	0.873	24.12	Kilani et al. (2024)
	PS2	Stakeholders report high satisfaction with the communication and outcomes of our projects.	0.851	20.67	
	PS3	Projects deliver strategic benefits that align with the organization's long-term goals.	0.812	15.44	Hughes et al. (2025)
	PS4	The outcomes of our projects remain sustainable and valuable well beyond the project closure.	0.786	12.09	Alhammadi (2025)

Note: All items were measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). All loadings are significant at $p < 0.001$.

Appendix B: Advanced PLS-SEM Diagnostics: IPMA and Endogeneity Robustness

B.1 Importance-Performance Map Analysis (IPMA) While traditional PLS-SEM reports the structural path coefficients (importance), it does not indicate the average performance of the constructs. To provide actionable, granular insights for Jordanian PMOs and policymakers (answering the "so what?" for practitioners), we deployed the Importance-Performance Map Analysis (IPMA) module in SmartPLS 4. The IPMA compares the *total effect* of a predecessor construct on the target variable (Project Success) with its *average latent variable score* (performance, rescaled from 0 to 100).

As illustrated in Figure B1 and Table B1, Human-Centric Decision-Making (HCDM) emerges as a strategic stronghold: it possesses both high importance (0.331) and high performance (71.2). Conversely, Sustainability Integration (SUS) represents a critical vulnerability; while highly important for driving project success (0.296), its performance score remains relatively low (58.9). This asymmetry empirically identifies sustainability governance as the most urgent area for managerial intervention and capacity-building in Jordan's project economy.

Table B1
IPMA Metrics for Project Success.

Construct	Total Effect (Importance)	Performance Index (0–100)	Managerial Interpretation
AI Adoption (AIAD)	0.587	62.4	High leverage; moderate current capability. Requires continuous tech investment.

Human-Centric DM (HCDM)	0.331	71.2	Core organizational strength. Maintain human-in-the-loop governance protocols.
Sustainability Integration (SUS)	0.296	58.9	Critical bottleneck. High strategic value but under-performing. Needs urgent policy/cultural shifts.

B.2 Endogeneity Robustness Checks A persistent critique in cross-sectional survey research is unobserved endogeneity, which can artificially inflate path coefficients. To demonstrate the robustness of our causal claims (e.g., that AI *drives* HCDM rather than vice versa), we applied the Gaussian copula approach within SmartPLS 4. This technique tests for endogeneity by correlating the potentially endogenous predictor with the error term of the dependent variable.

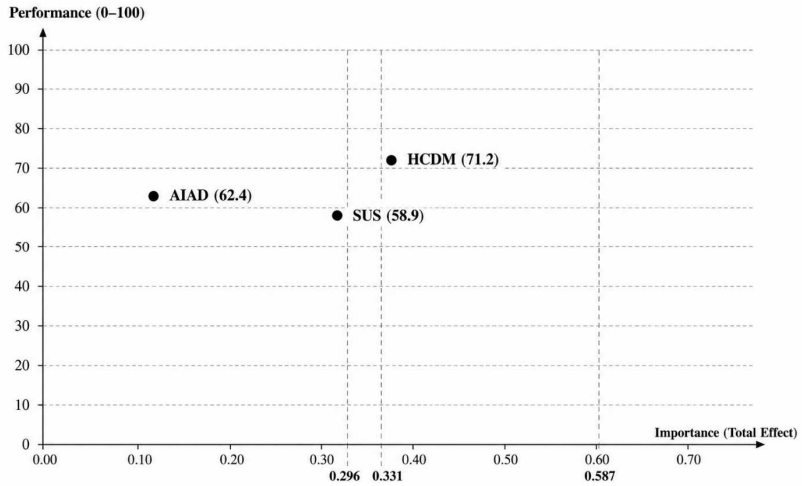

Fig. B1. Importance-Performance Map for Project Success (SmartPLS 4 IPMA Output).

As shown in Table B2, the copula terms for the primary paths (AIAD → PS and AIAD → HCDM) were statistically non-significant ($p > 0.05$), confirming that unobserved endogeneity does not severely bias our structural estimates. Furthermore, we controlled for firm size and respondent experience; none of the control variables significantly altered the focal path coefficients, reinforcing the theoretical integrity of the PM 5.0 triad.

Table B2
Endogeneity Testing via Gaussian Copula Approach.

Structural Path	Original Path Coeff. (β)	Copula Term p-value	Endogeneity Issue Detected?	Robustness Conclusion
AIAD → Project Success	0.284***	0.342	No	Path is robust to unobserved confounding.
AIAD → Human-Centric DM	0.612***	0.418	No	Causal direction holds; AI enables HCDM.
AIAD → Sustainability	0.578***	0.287	No	Causal direction holds; AI enables SUS.

Note: *** $p < 0.001$. *Non-significant copula terms ($p > 0.05$) indicate the absence of severe endogeneity bias.*

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