Received 6 March 2025
Revised 26 May 2025
8 July 2025
Accepted 8 July 2025

Harnessing AI for value: examining the impact of AI capabilities and the mediating role of organizational agility on project value proposition

Costanza Mariani and Mauro Mancini
Department of Management, Economics and Industrial Engineering, Politecnico di Milano, Milan, Italy

Abstract

Purpose – Recent advancements in artificial intelligence (AI) have transformed it from a mere technological tool to a key strategic asset, able to enhance company value propositions by enabling deeper insights, improved decision-making and innovative business models. This study empirically examines how AI capabilities influence value definition, creation and capture in project-based organizations (PBOs) and evaluates the mediating role of organizational agility.

Design/methodology/approach – Drawing on Resource-Based View and Dynamic Capability View, we propose that AI capabilities constitute a unique type of organizational capability, enabling project-based organizations to utilize technological assets and other resources to boost productivity and generate economic value. The paper employs a survey instrument and a partial least squares structural equation modeling (PLS-SEM) to assess how AI capabilities impact project value processes and the mediating role of organizational agility in this relationship.

Findings – The results robustly support all proposed hypotheses concerning the direct effects. Additionally, organizational agility is identified as a mediator in the relationship between AI capabilities and project value processes. Our study confirms that developing robust AI capabilities necessitates strategic investment in core AI resources. This offers implications for managers and policymakers aiming to leverage AI for fostering competitive advantage.

Originality/value – This paper explores the role of AI capabilities in enhancing project value processes. It provides empirical evidence highlighting the significance of AI capabilities as essential organizational resources that enable the leveraging of AI to generate project value. The study supports the hypothesis that technology alone is insufficient for deriving value from it. This finding underscores the need for strategic investments in AI capabilities to fully capitalize on the potential of technological advancements.

Keywords AI capabilities, Project value processes, Organizational agility

Paper type Research article

1. Introduction

Over the past few years, artificial intelligence (AI) – intended as a system's ability to perceive, interpret and learn from data to support decision-making and organizational goals – has become a major technological focus for organizations, driven by the widespread availability of big data, along with advances in innovative methods and infrastructure (HAI Stanford, 2024). A recent McKinsey report highlights a significant surge in AI adoption across various organizations. For the past six years, the adoption rate among global respondents' organizations had remained steady at approximately 50%. However, the 2024 survey reveals a substantial increase, with adoption rates soaring to 72%. This uptick indicates a robust, widespread enthusiasm for AI technologies globally (McKinsey, 2024). However, a study by MIT Sloan indicates a contrasting trend in the practical impact of AI and machine

International Journal of Managing Projects in Business
Vol. 18 No. 8, 2025
pp. 112-143
Emerald Publishing Limited
e-ISSN: 1753-8386
p-ISSN: 1753-8378
DOI 10.1108/IJMPB-03-2025-0068

learning (ML) technologies. Despite the wide range of potential applications these technologies offer to various industries, the data suggest that their integration has yet to yield substantial business value for a majority of companies. Specifically, 70% of organizations report that AI has had minimal impact on their business operations and 87% of AI projects never advance to the production stage (MIT Sloan, 2024). This trend is also reflected in the project management literature, where the anticipated impact of AI on project business models is discussed but has not yet been empirically investigated (Fridgeirsson *et al.*, 2021; Holzmann *et al.*, 2022).

Some scholars believe that the failure of AI to meet anticipated outcomes is primarily due to delays in its implementation and the necessary organizational adjustments (Braojos *et al.*, 2019). Companies need to commit to investing in resources that complement their AI technologies because these essential capabilities are key to unlocking the potential benefits of AI (Mikalef and Gupta, 2021; Sahoo *et al.*, 2024). This shift highlights the critical need to examine how organizations can effectively develop AI capabilities and determine the key resources they must depend on to support their development (Mikalef and Gupta, 2021).

Within the project management literature, it is recognized that for maintaining competitiveness through ongoing value creation within the project, as well as its delivery and sustained capture post-completion, project-based organizations (PBOs) need capabilities and key organizational resources (Lobo and Whyte, 2017; Mainga, 2017; Moradi *et al.*, 2020). Building on resource-based view (RBV) and dynamic capabilities view, we argue that AI capabilities are a distinct form of organizational capabilities that allow PBOs to leverage technological assets and other resources to enhance productivity and create economic value. These theoretical frameworks offer a systematic method to evaluate how AI capabilities impact a PBO organization's ability to define, create and capture value, which crucially depends on the quality and alignment of the underlying resources.

Despite the expanding body of literature that has explored the strategic value of digital transformation on project business and delivery models (Papadonikolaki *et al.*, 2022; Ngereja *et al.*, 2024; Mariani *et al.*, 2025b), the debate regarding the potential of AI capabilities to impact project value remains open and calls for further research development. One of the gaps in project management literature has been the tendency to view AI predominantly as a technological advancement rather than a business capability. While there is an abundance of papers assessing the impact of specific AI techniques on project management (PM) processes (Costantino *et al.*, 2015; Mancini *et al.*, 2023; Mariani *et al.*, 2023), to the best of the authors' knowledge, there are none that conceptualize AI as an inherent business capability. This oversight limits the understanding of AI's broader role and potential benefits in enhancing business competitiveness and strategic goals. Additionally, the literature has predominantly focused on technological capabilities from an internal perspective, neglecting the role of customers and external stakeholders in strategically leveraging these capabilities (Korotkova *et al.*, 2024; Zhang, 2024). This oversight has led to an expanding gap in the literature regarding the conceptual linkage between AI and other theoretical aspects of projects delivery like project value proposition.

To address this gap and enhance our understanding of the "outward" impact of AI capabilities, we draw upon the frameworks of Bowman and Ambrosini (2000) and Lepak *et al.* (2007). Here, value is defined as the perceived capability of a product, service or system to satisfy the needs of the target user or stakeholder. Thus, value is considered to specifically pertain to a stakeholder or a group of stakeholders. In strategy literature, a business model is commonly defined by three fundamental processes: value definition, value creation and value capture (Chesbrough and Rosenbloom, 2002; Chesbrough, 2007). Drawing on established research in PM literature (Miterev *et al.*, 2020), our paper employs these three distinct processes – collectively defined as *mechanisms of project value realization*, to assess the impact of AI capabilities. Considering the broad agreement that these processes are inherently different (Miterev *et al.*, 2020), our research seeks to explore the following question.

RQ1. What is the impact of AI capabilities on project value definition, value creation and value capture?

Previous research emphasizes that agility is considered a critical dynamic capability for leveraging emerging digital trends (Ciric Lalic *et al.*, 2022; Manurung and Kurniawan, 2022; Kadenic and Tambo, 2023). Authors suggest that rapid decision-making and agility are crucial for capitalizing on technological advancements (Fosso Wamba, 2022). These qualities enable companies to explore new markets, technologies and skills beyond their existing capabilities, offering access to external knowledge and resources. This, in turn, helps organizations maintain competitive business models and accelerate innovation (Akhtar *et al.*, 2018; Chan *et al.*, 2019). This is proved to be valid also for PBOs (Manurung and Kurniawan, 2022), thus it is important for our study to examine how this trait affects the interaction between AI capabilities and the previously defined value processes. To this end, we pose the following research question.

RQ2. To what extent does agility intervene in the relationship between AI capabilities and project value definition, creation and capture?

To the authors' knowledge, there has yet to be a study that examines the intervening role of organizational agility in the relationship between AI capabilities and project value processes, a gap that could have significant implications for both practitioners and policymakers. To address the research questions, this study utilizes a survey methodology and conducts a partial least squares structural equation modeling (PLS-SEM) analysis. The remainder of the paper is organized as follows. The next section provides the theoretical foundation and research model central to this investigation, including the proposed hypotheses. The third section details the methodology employed, while the fourth section presents the results from the PLS-SEM analysis. This approach tests the strength of relationships among the model components, enhancing our understanding of the dynamics at play and offering insights for practitioners and decision-makers on optimizing project value processes. The fifth section discusses the findings of the multi-group analysis (MGA), while section six discusses the paper findings emphasizing their theoretical and practical implications. The paper concludes with an examination of the research limitations and suggests directions for future research.

2. Theory and hypothesis development

2.1 Resource-based view and dynamic capabilities

The RBV is a known framework in strategic management literature that explains why firms with similar market conditions can have different performance levels. It argues that a firm's competitive edge comes from its unique resources, which must be valuable, rare, hard to replicate and irreplaceable to foster performance improvements (Barney, 2001; Barney and Arikan, 2005). Later developments in RBV differentiate between selecting resources and building capabilities, which are key aspects of the theory. According to (Amit and Schoemaker, 1993), resources are seen as tradable, general firm assets, whereas capabilities are the non-tradable, specific skills that allow a firm to coordinate, manage and apply these resources effectively. Thus, resources are inputs in the production process, and capabilities represent the ability to utilize these resources to enhance productivity and create economic value. According to this viewpoint, which we build upon for our paper, the quality and effectiveness of a firm's capabilities are contingent on the underlying resources they are built upon (Makadok, 2001; Sirmon *et al.*, 2007). Building on this foundation, more recent work has highlighted the need to differentiate between operational capabilities (those enabling efficient, day-to-day functioning), dynamic capabilities (those allowing firms to adapt, integrate and reconfigure resources in response to change) and architectural capabilities, which enable firms to align and coordinate heterogeneous activities and resources across units and levels (Jacobides and Winter, 2005; Helfat and Peteraf, 2015). This layered understanding is particularly relevant to our conceptualization of AI capabilities, which we frame as embedded enablers composed of tangible, human and intangible elements. In fact, AI capabilities do not operate in isolation, but must be systematically coordinated across technical infrastructure, managerial skillsets and organizational routines to effectively support both adaptive responses and cross-functional integration, also in project-based settings (Mikalef and Gupta, 2021). These dimensions, when orchestrated effectively, may underpin not only the firm's operational functioning but also its capacity to reconfigure itself in response to shifting project environments—thus reflecting both dynamic and architectural roles (Helfat and Peteraf, 2015). The critiques of RBV's static ontology in rapidly evolving contexts (Krakowski *et al*., 2023) have highlighted the limitations of explaining organizational adaptation solely through the possession of valuable resources. Recent studies in strategic management suggest that AI, as a potentially transformative technology, is crucial for companies aiming to gain a competitive edge (Krakowski *et al*., 2023). It enables the discovery of new business models through the identification of opportunities in emerging technologies and the capture of new revenue streams associated with these technologies (Enholm *et al*., 2022). However, this process necessitates a thorough reconfiguration and realignment of a company's resources, organizational structure and strategic approach (Mikalef and Gupta, 2021). Extending this argument to PBOs and aligning with the evolution of the RBV into the Dynamic Capabilities View (DCV) (Teece, 2007), we suggest that the transformation of both PBOs' business model propositions and AI capabilities must be underpinned by the development of organizational competencies that enable sensing, seizing and reconfiguring resources in response to turbulent environments. These dynamic capabilities – particularly those related to orchestrating AI-related assets – represent a novel layer of organizational adaptation not previously addressed in the PM literature (Lobo and Whyte, 2017) and are critical to sustaining competitive advantage through the effective development and deployment of AI capabilities. Within this dynamic capabilities' perspective, the inclusion of organizational agility in our framework further reinforces the firm's ability to translate AI investments into meaningful value outcomes. Agility is understood as a higher-order dynamic capability that enhances the firm's capacity to sense changes, respond rapidly and reconfigure resources proactively in dynamic environments (Ciric Lalic *et al*., 2022; Kadenic and Tambo, 2023). In project-based organizations, where uncertainty and complexity are inherent, agility functions as an amplifier and enabler of AI capabilities, allowing firms to adapt business models, processes and stakeholder engagement practices in real time (Mariani *et al*., 2025a). By modeling agility as a mediating mechanism, we aim to capture how AI capabilities interact with organizational routines and decision-making processes to support value definition, creation and capture in volatile project contexts. In summary, our theoretical framework draws on both the Resource-Based View (RBV) and the Dynamic Capabilities View (DCV) to capture the dual nature of AI capabilities in project-based organizations. The RBV provides a foundational lens to conceptualize AI capabilities as valuable, rare and difficult-to-imitate bundles of tangible, human and intangible resources that can contribute to sustained competitive advantage. However, recognizing the limitations of RBV's static ontology in rapidly evolving technological and organizational contexts, we integrate the DCV to explain how firms can dynamically deploy, reconfigure and orchestrate these capabilities in response to environmental turbulence. This combined perspective allows us to conceptualize AI not merely as a resource, but as an embedded, evolving organizational enabler – activated and amplified through agility – to shape project value outcomes.

2.2 Research model and hypothesis development

Our theoretical background is organized around three core dimensions: (1) the conceptualization and nature of AI capabilities (tangible, human and intangible), (2) their impact on the mechanisms of project value realization (definition, creation and capture) and (3) the role of organizational agility as a dynamic capability that mediates this relationship.

2.2.1 The AI capabilities construct. Although AI has been a subject of interest for many years, the literature still lacks a universally accepted definition. This absence of a consistent definition to anchor empirical research on AI has resulted in a fundamental challenge in fully understanding it (Marr, 2018). A common focus across various definitions of AI is its aim to mimic human learning mechanisms, process information and address states that necessitate problem-solving (Haenlein and Kaplan, 2019). Following this line of argumentation, scholars have recently characterized AI as a system's capability to identify, interpret, draw inferences and learn from data in order to accomplish predefined organizational and societal goals (Mikalef and Gupta, 2021). Based on this definition, AI represents an interdisciplinary field that unveils a new arena of opportunities with practical implications for both businesses and society at large. Narrow AI, also known as weak AI, refers to AI systems designed to handle specific tasks or problems – unlike general AI, which can perform any cognitive task that a human can. Narrow AI is currently the common form of AI in practical business applications, excelling at defined and structured tasks (Haenlein and Kaplan, 2019). Despite the relatively sparse research on the business value and application of AI within organizational settings, some studies have pinpointed challenges associated with successfully deploying AI projects (Volkmar *et al.*, 2022). Even though the AI-specific technology needed to support these initiatives is expected to advance rapidly, it is equally crucial to focus on nurturing other organizational capabilities beyond just the technology (Mikalef and Gupta, 2021; Abou-Foul *et al.*, 2023). These complementary skills are understood as those that enable an organization to leverage technology for value creation. This has prompted scholarly research to further elaborate on the concept of AI capabilities. Table 1 provides a summary of the definitions of AI capabilities.

The studies mentioned, along with various academic articles and business reports, underscore the range of resources that organizations must develop to extract business value from their investments in AI. Mikalef and Gupta (2021) suggest that the foundation of AI capabilities consists of tangible, intangible and human resources. Tangible resources encompass data, technology and basic infrastructural elements. Human resources include both business acumen and technical expertise. Additionally, inter-departmental collaboration, the ability to adapt to organizational change and a willingness to take risks are highlighted as three essential intangible resources that are crucial for developing AI capabilities.

Table 1. AI capabilities definitions

Authors	Definition
Schmidt *et al.* (2020)	AI capability is the ability of organizations to use data, methods, processes and people in a way that creates new possibilities for automation, decision making, collaboration, etc. that would not be possible by conventional means
Schmidt *et al.* (2020)	AI-capabilities are digital capabilities that integrate AI-specific assets, for instance, AI-algorithms, training data, etc. in order to enable value creation
Wamba-Taguimdje *et al.* (2020)	AI capabilities could be defined as the firm's ability to create a bundle of organizational, personnel and AI resources for business value creation and capture
Mikalef and Gupta (2021)	An AI capability is the ability of a firm to select, orchestrate and leverage its AI-specific resources
Sjödin *et al.* (2021)	AI Capabilities are technical enablers of new services and products
Gama and Magistretti (2023)	AI Capabilities are the skills and knowledge needed to effectively absorb, master and improve AI technologies and to create new ones
Sahoo *et al.* (2024)	AI Capabilities refer to an organization's utilization of cognitive computing technologies, proprietary data analytics, machine learning algorithms and interactive dashboards to enhance strategic decision-making across functional domains, facilitating the interpretation of complex information and enabling seamless access to critical insights for informed decision-making by process administrators and managers

Source(s): Authors' elaboration

2.2.2 AI capabilities and project value definition. Project value definition is defined as the process of identifying and understanding the value that a project, product or service provides to its stakeholders, based on their needs and expectations (Miterev *et al.*, 2020). In PM literature, the process of value definition is often understood to consist of two key aspects: value sense-making and value formalization (Martinsuo and Hoverfält, 2018; Martinsuo *et al.*, 2019). The value sense-making phase focuses on understanding stakeholder needs, performing international benchmarking studies and market research to evaluate the potential benefits of future projects. Value formalization represents a more structured phase where core stakeholders define the mission and vision. This stage serves to formally solidify the value-related outcomes and requirements, transforming the collaborative insights from the sense-making process into a clear and cohesive strategic framework.

Developing AI capabilities can enable organization that operates by projects to gain deeper insights into customer needs and preferences (Walker and Lloyd-Walker, 2019; Mariani *et al.*, 2023), allowing them to customize their projects more effectively to meet those specific demands. For example, in construction projects, research has shown that data mining has been employed to conduct comprehensive market research, helping organizations analyze vast amounts of data to identify patterns, trends and customer preferences (Yan *et al.*, 2020). This allows businesses to understand whether certain types of projects or services are more profitable or have higher potential for success compared to others (Costantino *et al.*, 2015; Elnabwy *et al.*, 2024). AI can assist businesses in discovering new opportunities for revenue growth by enhancing stakeholder analysis strategies and optimizing the selection of products for their portfolio (Relich and Pawlewski, 2017; Jafarzadeh *et al.*, 2018; Byrum, 2022). Further the literature has empirically shown the contribution of building AI capabilities to the project value formalization processes. One of the areas where it is most widely applied is the stakeholder requirement elicitation process (Dam *et al.*, 2019; Arora *et al.*, 2024). Natural language often presents challenges such as verbal ambiguity and syntactic vagueness. To address these issues, researchers have explored the use of Natural Language Processing (NLP) in the requirements elicitation process (Anwar and Bashir, 2023). For example, syntactically driven parsing, which groups words into higher-level units like sentences, phrases and clauses allows for better understanding and interpretation of language (Frank *et al.*, 2012) resulting in a more accurate definition of stakeholder requirements. Additionally, there is extensive literature reporting how various AI techniques, such as derivatives of fuzzy logic like Fuzzy C-Mean (Ramzan *et al.*, 2011), neuro-fuzzy systems (Momeni *et al.*, 2014), optimization techniques (Alrezaamiri *et al.*, 2020) and machine learning (Hujainah *et al.*, 2021), can be employed to prioritize requirements in favor of customer needs. These techniques are also beneficial in cases of change requests during the project outcome definition phase (Naz *et al.*, 2013). Building on these arguments, we propose the following hypothesis:

H1. AI capabilities positively influence project value definition

2.2.3 AI capabilities and project value creation. Value creation in projects refers to the process of ensuring that a project achieves its intended outcomes and creates measurable benefits for its stakeholders (Miterev *et al.*, 2020). According to a recent literature stream, this encompasses not only delivering the predefined outputs within the project's scope, time and budget but also ensuring that these outputs contribute to long-term value creation (Laursen and Svejvig, 2016). This has led to a shift toward conceptualizing projects as vehicles of value creation (Laursen and Svejvig, 2016; Martinsuo and Hoverfält, 2018). Value creation involves aligning project goals with stakeholder needs, optimizing the use of resources and continuously evaluating and adjusting project efforts to maximize both monetary and non-monetary benefits. It is a holistic approach that goes beyond the completion of tasks and focuses on the overall impact and sustainability of the project's outcomes for all involved parties (Haddadi *et al.*, 2017; Svejvig *et al.*, 2019; Sjödin *et al.*, 2020). Literature has shown that building AI capabilities can have positive impacts on project value creation. Case-based reasoning, genetic algorithms and artificial neural networks have been proposed as viable alternatives for the execution of projects' schedule planning processes (Faghihi *et al.*, 2015). ANN and Support Vector Machines models can predict project schedules based on early planning status updates (Wang *et al.*, 2012; Wauters and Vanhoucke, 2014). AI is increasingly being applied in project budgeting, particularly in predicting cash flows and estimating costs (Cheng *et al.*, 2010; Cheng *et al.*, 2015; Inan *et al.*, 2022). AI is used effectively for forecasting resource effort estimates by employing ANN, KNN multiple regression to estimate the necessary resource effort for specific project tasks (Bisi and Goyal, 2016; Polkowski *et al.*, 2019), Also, Ant Colony Optimization (Myszkowski *et al.*, 2015) and other optimization algorithms (Cheng and Yan, 2009; Peng and Liu, 2022) are employed to solve resource optimization problems. AI applications in project risk management predominantly present models applied during the risk assessment phase or to select the best set of mitigation actions (Khakzad *et al.*, 2013; Mancini *et al.*, 2023; Mariani and Mancini, 2023). Besides, AI can forecast potential long terms outcomes and expected completion dates for projects, enabling project managers to foresee obstacles and implement preemptive strategies (Flyvbjerg *et al.*, 2022). AI supports in estimating the Estimate at Complention (EAC) (Cheng *et al.*, 2019) and to and to perform the earned value analysis (Acebes *et al.*, 2015). Overall, AI capabilities contribute to project value creation by enhancing planning, control and execution across various PM processes. Furthermore, recent literature has explored the use of AI in achieving long-term sustainable outcomes, particularly in the construction sector, highlighting how this technology can also be employed to realize long-term sustainable project outcomes (Baduge *et al.*, 2022; Regona *et al.*, 2024). Thus, we put forward the following hypothesis:

H2. AI capabilities positively influence project value creation

2.2.4 AI capabilities and project value capture. Value capture is commonly defined as the difference between the revenues and the costs retained by a firm (Bowman and Ambrosini, 2000, 2010; Mol *et al.*, 2005) and it refers to the process by which firms retain a part of the value they create (Zott and Amit, 2010; Bos-de Vos *et al.*, 2019). In the field of PM, scholars distinguish value capture as a process separate from value creation (Laursen and Svejvig, 2016; Miterev *et al.*, 2020) noting that value capture extends all over the project lifecycle (Chang *et al.*, 2013). Bowman and Ambrosini (2000) differentiate between use value, which is the customer's subjective perception of a product's qualities and exchange value, which is the actual price paid by the customer that the company is able to retain. In addition to monetary gains, PBOs rely on generating and retaining non-monetary value aspects to ensure long-term sustainable competitiveness. Key non-monetary value dimensions highlighted in PM studies include project quality, client satisfaction, knowledge development and sharing, societal impact and enjoyment (Bos-de Vos *et al.*, 2019; Lehtinen *et al.*, 2019). Recent research has empirically demonstrated that AI applications and capabilities can contribute to both monetary and non-monetary project value capture. For example, AI systems enhance the precision of conceptual cost estimates by leveraging data from previous projects (Cheng *et al.*, 2010). This capability acts as an early warning system, enabling decision-makers to anticipate potential issues and optimize the return on investment (ROI) by circumventing unnecessary expenditures (Baduge *et al.*, 2022; Li and Zuo, 2024). AI-driven simulation models have been used to create virtual scenarios that help in decision-making processes. These simulations are employed to optimize project outcomes by exploring various "what-if" scenarios, allowing project managers to make decisions based on comprehensive data analysis and potential outcome predictions (Zhao *et al.*, 2022). Evolutionary algorithms, such as genetic algorithms, are used in construction and engineering to optimize project finances by minimizing costs and durations, balancing expenses and ensuring resource allocation meets financial constraints (Abdel-Khalek *et al.*, 2017; El-Abbasy *et al.*, 2020). Further, ANNs and fuzzy algorithms, have proved to be effective in facilitating the identification of projects that promise the greatest maximization of monetary capture (Costantino *et al.*, 2015). In this way, investments are strategically directed towards projects with the highest potential ROI. This reduces the risks associated with investing in less profitable or uncertain projects (Ghorbani and Rabbani, 2009;

Taylan *et al.*, 2014). In building and construction, the use of ANN and genetic algorithms in controlling processes and communication between stakeholders leads to fewer reworks, thereby reducing value slippage and enhancing customer satisfaction (Hossain and Chua, 2014; Trach *et al.*, 2021). Moreover, AI can enable new revenue models, such as subscription services or platform-based ecosystems, allowing companies to capture value in innovative ways (Teece, 2018). Beyond monetary optimization, AI technologies can strengthen customer relationships and satisfaction and improve knowledge management inside the organization. By anticipating retention and offering individualized services, data mining and Random Forest algorithms can increase customer loyalty, forging closer bonds with clients and raising overall contentment (Libai *et al.*, 2020). Additionally, AI-powered knowledge management systems enhance the ability of PBOs to gather, process and share knowledge effectively. Machine learning and neural networks automate these processes, preserving insights and facilitating continuous learning, which is crucial for long-term value retention (Malik *et al.*, 2021; Taherdoost and Madanchian, 2023). We thus put forward the following hypothesis.

H3. AI capabilities positively influence project value capture

2.2.5 The mediating role of organizational agility. Organizational agility can be conceptually articulated around two core dimensions: flexibility, understood as the ability to anticipate and prepare for change and adaptability, defined as the capacity to make timely and informed adjustments in response to environmental dynamics (Harraf and Wanasika, 2015). This distinction aligns closely with the microfoundations of DCV, where flexibility maps onto sensing, adaptability reflects responding and the capacity to sustain iterative transformation resonates with reconfiguring or adapting capabilities (Tallon *et al.*, 2019). In today's intensely competitive market, organizational agility is becoming an essential asset (Gligor *et al.*, 2015; Shams *et al.*, 2021; Ferraris *et al.*, 2022) that facilitates innovation and secures a competitive edge (Santos *et al.*, 2025). With the rise of disruptive digital technologies, organizational agility has become even more crucial (Trost, 2020; Kiani, 2024). In fact, recent research increasingly positions organizational agility as a critical enabler for firms seeking to unlock the value of digital technologies (Akhtar *et al.*, 2018; Chan *et al.*, 2019; Chan *et al.*, 2019). In the context of IS agility is seen not merely as a technological attribute but as a strategic capability that allows organizations to sense opportunities, respond rapidly to feedback and adapt business models in dynamic environments (Fosso Wamba, 2022). Werder *et al.* (2021) highlight that agility acts as a leveraging mechanism, amplifying the performance effects of IT through business model renewal and process adaptation. Lee *et al.* (2015) also report that agility reinforces IT investments at the operational level and helps firms take advantage of operational opportunities, adapt to changing internal and external conditions and maintain a competitive operational advantage, thus leading to improved firm performance. Previous research has reported that organizational agility mediates the relationship between investments in AI technologies and firm outcomes (Fosso Wamba, 2022). The hypotheses derived from firm-level literature suggest that this line of argumentation can be extended to PBOs, where organizational has a significant impact on how value is realized within projects (Conforto *et al.*, 2016). We hypothesize that organizational agility mediates the relationship between strategic investments in AI capabilities and their successful value definition, creation and capture. This mediation allows for the effective transformation of AI capabilities into tangible project benefits, thus enhancing value processes. Consequently, agility not only facilitates the use of AI but also ensures that its deployment is adaptive and responsive to the evolving project requirements and external pressures (Ambituuni *et al.*, 2021). Thus, we propose that while AI capabilities have a positive impact on project value processes, it is the agility of the organization that determines how effectively these technologies are leveraged to define, create and capture value within projects. In this sense, agility serves as a dynamic capability that connects the potential of AI technologies with the realization of value across the project lifecycle. Therefore, we propose the following hypothesis:

H4. Organizational agility positively mediates the impact of AI capabilities on project value definition, creation and capture.

3. Research method

The present study employs a quantitative analysis, gathering responses from participants working in project contexts. These participants offer insights into survey questions drawn from their own observations. Below, the methodological section elaborates on this research philosophy, detailing the development of the research instrument, the approach to data collection, issues related to common method variance, sample adequacy and the analysis software used. Figure 1 shows the research framework employed for the analysis. All constructs were modeled reflectively, following current PLS-SEM guidelines for conceptually coherent and empirically correlated dimensions (Hair *et al.*, 2019; Sarstedt *et al.*, 2019). In particular, AI Capabilities was specified as a second-order reflective–reflective construct composed of Tangible, Human and Intangible subdimensions, to ensure theoretical fidelity and alignment with prior research (Mikalef and Gupta, 2021).

3.1 Research instrument

This study utilized a survey method and crafted a research instrument to collect data. The instrument was split into two parts: the first section collected demographic details of respondents, including their role, years of experience, the sector their organization operates in and the number of employees in their organization. The second section was designed to gather perceptions on topics concerning AI capabilities and project value processes. The second part of the research instrument was designed drawing from prior research, incorporating and adapting to the project context, concepts and survey questions about AI capabilities (Mikalef and Gupta, 2021), project value processes (Miterev *et al.*, 2020; Laursen and Svejvig, 2016; Martinsuo and Hoverfält, 2018) and organizational agility (Fosso Wamba, 2022; Ambituuni *et al.*, 2021). The survey instrument, which is reported in the Appendix, included 10 items for AI capabilities, which were conceptually grouped into three sub-dimensions – Tangible (5 items), Human (3 items) and Intangible (2 items) – and modeled as a second-order reflective–reflective construct. Additionally, the instrument included five items for value

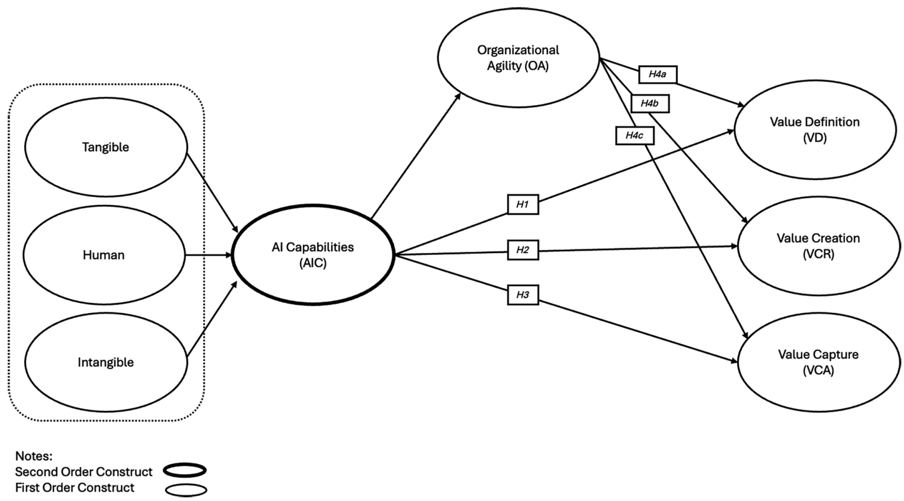

Figure 1. Conceptual research model linking AI capabilities, organizational agility, and project value dimensions. Source: Authors' elaboration

definition, four items for both value creation and organizational agility and five items for value capture. We gathered input from three academic experts specialized in PM research and three industry experts to refine the research instrument, ensuring the questions were suitable for accurately measuring the constructs (Sireci, 1998; Mackenzie *et al.*, 2011). Additionally, nine project professionals participated in an online focus group to validate the proposed instrument. After consulting with all the mentioned reviewers, we chose to use a five-point Likert scale for perception-based items, ranging from 1 (strongly disagree) to 5 (strongly agree).

3.2 Data and sample

After finalizing the questionnaire, we focused on gathering data from appropriate respondents, employing a judgment-based sampling method to do so. We employed the databases AIDA (Italian) and Orbis (International) to assemble a list of 300 international PBOs primarily engaged in project-based working. We reached out to organizations using the contact information available in the databases, reaching out primary via email. When we successfully established communication, we explained the research context and expressed the intention to connect with senior management experienced in project work. If the initial contact was delayed or unresponsive, we then used LinkedIn to find potential project professionals within these organizations who could respond to the survey. Following this method, we successfully collected data from 167 project professionals within PBOs, with their demographic profiles detailed in Table 2, resulting in a 56% effective response rate. We administered the survey via Microsoft Teams, scheduling sessions according to each respondent's availability. After setting up the virtual meeting, the survey link was shared through the Teams chat. Each

Table 2. Demographic and company profile of survey respondents

Firms size	#Number Category	Percentage Number
≤50	79	47%
≤250	30	18%
>250	58	35%
Location		
Italy	68	41%
Europe	86	51%
World	13	8%
Industry		
Construction	40	24%
Engineering	50	30%
Energy	16	10%
Transportation	13	8%
IT	48	29%
Working experience of respondents (years)		
≤5	4	2%
5 10	29	17%
10 20	84	50%
>20	50	30%
Respondent work position		
Project manager	45	27%
Senior project manager	50	30%
Program manager	37	22%
Director/portfolio manager	35	21%

Source(s): Authors' elaboration

question was carefully presented to the respondents, who were given time to reflect and respond using the five-point Likert scale. This approach was designed to ensure respondents thoroughly understood each question's context and could provide well-considered answers. We guaranteed anonymity regarding personal and organizational information to encourage forthright responses. This method and the direct administration of the survey minimized sample selection bias. Data collection was conducted from February to October 2024.

3.3 Sample adequacy

It is essential to assess the minimum sample size required in order to ensure that the PLS-SEM results have adequate statistical power, allowing for robust results. To address this, we used different approaches suggested by Hair *et al.* (2017) including: the 10-time rule, the power analysis method and the inverse square root. The first method used to verify the sample size is the 10-times rule, which states that the sample must be at least 10 times the number of independent variables in the most complex regression in the PLS path model considering both measurement and structural models. In our model, the most complex construct is AI capabilities which has 11 indicators; therefore, the minimum sample size would be 110. However, the minimum sample size should consider also the statistical power. We used the G*Power software considering a statistical power of 80% and a medium effect size (f^2) of 0.15, resulting in 77 observations required (Faul *et al.*, 2009; Hair *et al.*, 2017). In light of the results obtained from the three approaches described, we conclude that our sample of 167 responses from the questionnaire is sufficient to ensure that our analysis has adequate statistical validity.

3.4 Biases analysis

In survey-based empirical research, common method variance (CMV) refers to the variation among variables that arises from the measurement method itself, rather than from the constructs intended to be measured. This presents a potential threat to the validity of the research findings (Hair *et al.*, 2017). The Harman single-factor test, used in the PLS-SEM context, serves as a diagnostic tool to assess the potential presence of common method bias or method variation in collected data (Fuller *et al.*, 2016; Aguirre-Urreta and Hu, 2019). This method involves conducting an exploratory factor analysis on the observed variables within a specific model. The aim of this analysis is to identify whether a single dominant factor arises, which could explain a significant amount of the variance observed in the data (Fuller *et al.*, 2016). In our study, the results of Harman's test revealed that the first principal component accounted for only 30.82% of the total variance, indicating that no single factor dominated the variance. This suggests that common method bias was not a concern in our study, as no single construct explained the majority of the variance. Additionally, we performed a principal component factor analysis (PCA) using all study variables and the results confirmed that variance was distributed across multiple components, reinforcing the validity of the data and reducing concerns about inflated relationships due to method bias (Hair *et al.*, 2017). It is fundamental to highlight that to avoid central tendency bias, as well as for improved data quality and measurement accuracy, we slightly shifted the neutral answer to the disagreement side. We avoided reducing the scale to an even number of choices in order to ensure not to force a choice, which would have backfired by potentially increasing frustration or random answering (Kankaraš and Capecchi, 2024).We compared early and late responses to make sure there was no issue related to the late-response bias. We created two response groups, in particular the data has been divided into 49 early responses and 118 late responses based on the submission time and then we performed the Mann–Whitney *U*-tests for each of the study's questions and the corresponding constructs they were used to capture. There was no evidence of late-response bias in our sample since all *p*-values turned out to be above 0.05, meaning there were no discernible differences between the items and constructs (McKnight and Najab, 2010).

3.5 Analysis software

The research framework and hypotheses were analyzed using PLS-SEM via the Smart PLS4.0 software. PLS-SEM is often favored over traditional covariance-based structural equation modeling (CB-SEM) in cases where there is a small sample size, non-normal data distributions or a high number of variables – like in this study (Hair *et al.*, 2019). This method is particularly valuable in exploratory research focused on outcome prediction rather than theory testing (Hair *et al.*, 2017). PLS-SEM is also advantageous for assessing complex models involving latent variables and multiple manifest variables (Hair *et al.*, 2019). Moreover, PLS-SEM offers greater flexibility and efficiency compared to CB-SEM, which typically requires a larger sample size to ensure stable and reliable results (Hair *et al.*, 2017). Therefore, considering the exploratory nature of this study and the limited sample size, employing PLS-SEM with SmartPLS 4.0 was considered a good choice for analyzing the collected data.

4. Results

4.1 Measurement model

Evaluating the measurement model involves examining the factor loading for each item in the construct, assessing construct reliability, checking composite reliability and verifying both convergent and discriminant validity (Hair *et al.*, 2017). Factor loading, indicate a strong relationship between each latent variable (i.e. construct) and its observable variables (i.e. items), as they all exceed the threshold of 0.7, suggesting robust links (Sarstedt *et al.*, 2014; Hair *et al.*, 2017). The construct AI capabilities was modeled as a second-order reflective–reflective construct, composed of three theoretically grounded first-order dimensions: tangible, human and intangible resources. As shown in Table 3, each construct's Cronbach's alpha, composite reliability and Rho_A values surpass the 0.7 benchmark, demonstrating that the measurement model possesses reliable internal consistency (Hair *et al.*, 2017). Convergent validity is confirmed by average variance extracted (AVE) values greater than 0.5 for each construct, indicating a significant common variance among the indicators of each construct (Hair *et al.*, 2017). Table 4 confirms the discriminant validity of the measurement model. In fact, the HTMT ratio values fall under the cutoff of 0.85, underscoring a robust discriminant validity of the model (Hair *et al.*, 2017). Additionally, all variance inflation factor (VIF) values are below the recommended threshold of 3.3, indicating the absence of multicollinearity among indicators (Hair *et al.*, 2019).

4.2 Structural model

In PLS-SEM, the structural model represents the stage of analysis that assesses the relationships among the latent variables (constructs) (Hair *et al.*, 2017). This model is typically estimated through path analysis, which involves examining the coefficients of the paths that connect the latent variables. The bootstrapping procedure was conducted using 5,000 resamples with a two-tailed test at a 5% significance level and exact *p*-values were calculated based on the percentile bootstrap method implemented in SmartPLS. The results of the structural model testing are reported in Figure 2, with more details provided in Table 5. The investigation examined the direct and indirect effects in accordance with the specified mediation hypotheses. All VIF were checked to assess the potential for collinearity and were found to be less than the 3.3 threshold (Kock, 2015). All reported f^2 values exceed the minimum threshold of 0.02 (Cohen, 2013), indicating at least small effect sizes, while all Q^2 values are greater than zero, confirming the model's predictive relevance according to the Stone–Geisser criterion (Hair *et al.*, 2019). The path coefficients and the direct, indirect and total effects between the variables in the research framework were determined using a one-tailed bootstrapping test with 5,000 subsamples. The direct relationships among variables (i.e. AI capabilities → Value definition; AI capabilities → Value creation; AI capabilities → Value capture) showed statistically significant effects, confirming hypotheses H1, H2 and H3.

Table 3. Construct reliability and convergent validity

Construct	Items	Convergent validity	Composite reliability	Rho_a	AVE	R^2	VIF
AI capabilities	Second-order (Tangible, Human, Intangible)		0.900	0.880	0.640		1.20
Tangible	AIC1–AIC5 (Access to data, services, etc.)	✓	0.868	0.840	0.575		1.02
	AIC1: Access to data	0.701					1.01
	AIC2: Cloud-based services	0.702					1.01
	AIC3: Processing power	0.758					1.01
	AIC4: Data storage	0.700					1.00
	AIC5: Financial resources	0.773					1.02
Human	AIC6–AIC8 (Tech skills, AI experts, Business)	✓	0.877	0.860	0.705		1.04
	AIC6: Data scientists	0.827					1.01
	AIC7: AI experts	0.753					1.02
	AIC8: Business skills	0.787					1.01
Intangible	AIC9–AIC10 (Collaboration, Change readiness)	✓	0.825	0.810	0.700		1.01
	AIC9: Inter-departmental coordination	0.702					1.01
	AIC10: Organizational change capability	0.700					1.01
Organizational agility	OA1–OA4 (Customer, Adaptability, etc.)	✓	0.904	0.905	0.704	0.092	1.10
	OA1: Customer focus	0.724					1.10
	OA2: Openness to communication	0.859					1.10
	OA3: Flexibility and adaptability	0.882					1.11
	OA4: Decision-making rapidity	0.882					1.10
Value definition	VD3–VD7	✓	0.876	0.876	0.586	0.332	1.05
	VD3: Definition of customer requirements	0.770					1.04
	VD4: Market research completeness	0.765					1.05
	VD5: Competition awareness	0.781					1.06
	VD6: Industry involvement	0.733					1.03
	VD7: Differentiation	0.776					1.02
Value creation	VC1–VC4	✓	0.862	0.873	0.634	0.372	1.06
	VC1: Adherence to schedule	0.715					1.05
	VC2: Resource allocation	0.874					1.06
	VC3: Activities prioritization	0.878					1.08
	VC4: Project advancement monitoring	0.701					1.06

(*continued*)

Table 3. Continued

Construct	Items	Convergent validity	Composite reliability	Rho_a	AVE	R^2	VIF
Value capture	VP2–VP6	✓	0.865	0.875	0.584	0.458	1.09
	VP2: ROI	0.702					1.08
	VP3: Value slippage	0.790					1.09
	VP4: Customer satisfaction	0.833					1.10
	VP5: Brand loyalty	0.771					1.08
	VP6: Knowledge development and sharing	0.718					1.10

Source(s): Authors' elaboration

Second, we tested the second set of hypotheses H4 (a-b-c). The results show that organizational agility significantly mediates the relationship between AI capabilities and the value processes. The direct effect of AI capabilities on organizational agility ($\beta = 0.313$, $p < 0.001$) is significant, indicating that AI capabilities positively influence organizational agility. Moreover, organizational agility has a significant positive effect on value creation ($\beta = 0.445$, $p < 0.001$), value definition ($\beta = 0.436$, $p < 0.001$) and value capture ($\beta = 0.617$, $p < 0.001$), highlighting its critical role in value realization.

5. Multi-group analysis

5.1 Firm size

To understand how the relationships within our model vary depending on firm size, we divided the sample into three categories: 79 small firms (≤50 employees), 30 medium firms (≤250 employees) and 58 large firms (>250 employees). Before proceeding with the actual analysis, it was crucial to ensure that each group had a sufficient sample size. A power analysis performed using G*Power indicated that at least 36 observations per group were needed to ensure robust results, assuming a large effect size ($f^2 = 0.35$), a significance level of 5% and statistical power of 80% (Hair *et al.*, 2017; Hair and Ringle, 2021; Cheah *et al.*, 2023). However, the group of medium-sized firms did not meet this threshold, having only 30 observations, which led us to focus our analysis on comparing only small and large firms. To ensure comparability, it was necessary to verify measurement invariance using the MICOM (Measurement Invariance of Composite Models) procedure (Hair *et al.*, 2017; Hair and Ringle, 2021; Cheah *et al.*, 2023). This assessment involved three steps. The first step, configural invariance, ensured that the same model structure was used for both groups, which was automatically established using SmartPLS. Measurement invariance was assessed using the MICOM procedure. Configural and compositional invariance were confirmed and mean and variance equality were established for all constructs (Cheah *et al.*, 2023). Once the partial measurement invariance was established, the multi-group analysis was performed using Henseler's bootstrap-based approach (PLS-MGA) (Henseler *et al.*, 2016). The results (Table 6) show that the relationship between AI capabilities and organizational agility does not differ significantly between small and large firms. However, some important differences emerge in how these constructs influence value processes. Specifically, AI capabilities have a significantly stronger effect on value creation in large firms ($p = 0.002$), suggesting that larger organizations may be better positioned to convert technical capabilities into operational improvements. Conversely, organizational agility plays a more prominent role in small firms, where its impact on value creation is significantly greater ($p = 0.000$). A similar pattern is observed for value capture: while no statistically significant difference was found between small and large firms regarding the direct effect of AI capabilities ($p = 0.064$), organizational

Table 4. Discriminant validity – heterotrait-monotrait ratio

	AI capabilities	Tangible	Human	Intangible	Organizational agility	Value definition	Value creation	Value capture
AI capabilities	1.0	0.82	0.83	0.81	0.68	0.65	0.72	0.63
Tangible		1.0	0.75	0.74	0.6	0.58	0.66	0.55
Human			1.0	0.76	0.62	0.6	0.69	0.59
Intangible				1.0	0.61	0.59	0.67	0.56
Organizational agility					1.0	0.71	0.76	0.78
Value definition						1.0	0.74	0.69
Value creation							1.0	0.73
Value capture								1.0

Source(s): Authors' elaboration

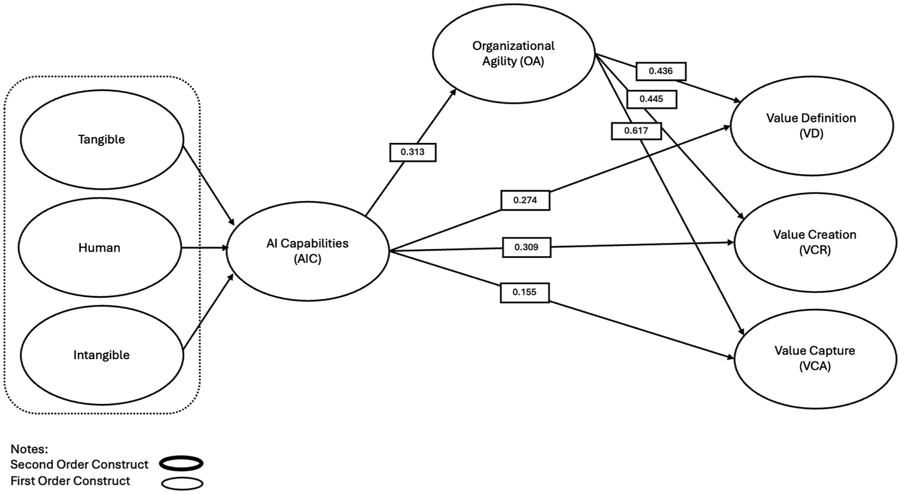

Figure 2. Results of direct and mediation hypotheses. Source: Authors' elaboration

agility once again shows a significantly stronger influence in small firms ($p = 0.004$). These findings highlight the critical role of agility in enabling smaller firms to realize value from AI investments.

5.2 Level of AI implementation

Another MGA was conducted to explore how different levels of AI implementation affect the relationships within our model. From our survey, we collected data on the level of AI implementation in each firm. Specifically, 44 firms reported that no action had been taken regarding AI, 30 firms were in the preliminary study phase, 16 firms were conducting technical-economic feasibility analyses, 26 firms had AI implementation in progress and 51 firms already had AI in use. We aggregated data to form two categories. The first category, "Low AI Implementation," combined firms that had taken no action or were in the early stages of feasibility analysis, totaling 90 firms. The second category, "High AI Implementation," comprised firms that had AI in progress or completed AI implementation, totaling 77 firms. The statistical power of the two groups was verified using G*Power, ensuring each group met the minimum requirement of 42 observations, assuming a medium effect size ($f^2 = 0.25$), a significance level of 5% and a power of 80% (Hair *et al.*, 2017; Hair and Ringle, 2021; Cheah *et al.*, 2023). Equality of means and variances was ensured, so we proceeded with the analysis. The comparison between firms with low and high levels of AI implementation (Table 7), based on PLS-MGA results, highlights several relevant differences. The relationship between AI capabilities and organizational agility was significantly stronger in firms with high AI implementation ($p = 0.042$), suggesting that organizations further along in their AI journey are more capable of converting technological resources into adaptive organizational behaviors. In these firms, AI capabilities also had a stronger influence on value creation ($p = 0.026$) and value definition ($p = 0.003$), indicating that the strategic benefits of AI become more apparent when implementation is more mature. Conversely, no significant differences emerged between the two groups regarding the relationship between AI capabilities and value capture ($p = 0.945$) or the effect of organizational agility on value creation ($p = 0.478$) and value capture ($p = 0.073$). These findings suggest that while higher AI maturity enhances certain organizational outcomes, other value-related effects may depend on additional enablers beyond implementation level.

Table 5. Results of structural model – direct and mediating effects

Hypothesis	Path	β	*p*-values	*t*-value	CI [2.5%–97.5%]	VIF	f^2	Q^2	Results
Direct effects									
H1	AI capabilities → Value definition	0.274	0.000	5.524	[0.212–0.435]	1.000	0.099	0.177	Supported
H2	AI capabilities → Value creation	0.309	0.000	2.341	[0.037–0.297]	1.108	0.103	0.321	Supported
H3	AI capabilities → Value capture	0.155	0.019	3.631	[0.071–0.239]	1.108	0.038	0.227	Supported
Mediated effects									
H4*	AI capabilities → Organizational agility	0.313	0.000	3.602	[0.134–0.432]	1.108	0.092	0.265	Supported
H4a*	Organizational agility → Value definition	0.436	0.000	7.909	[0.439–0.742]	1.108	0.241	0.177	Supported
H4b*	Organizational agility → Value creation	0.445	0.000	5.282	[0.274–0.599]	1.108	0.182	0.321	Supported
H4c	Organizational agility → Value capture	0.617	0.000	4.849	[0.236–0.590]	1.108	0.347	0.227	Supported

Source(s): Authors' elaboration

Table 6. MGA on firm size results

	Path coefficient (small)	Path coefficient (large)	Difference (small–large)	2-Tailed (small vs large) *p*-value
AI capabilities → Organizational agility	0.411	0.266	0.146	0.271
AI capabilities → Value definition	0.296	0.409	−0.113	0.397
AI capabilities → Value creation	0.151	0.595	−0.444	0.002
AI capabilities → Value capture	0.056	0.338	−0.282	0.064
Organizational agility → Value definition	0.503	0.236	0.267	0.133
Organizational agility → Value creation	0.676	0.126	0.549	0.000
Organizational agility → Value capture	0.802	0.360	0.443	0.004

Source(s): Authors' elaboration

Table 7. MGA on level of AI implementation

	Path coefficient (low)	Path coefficient (high)	Difference (low- high)	2-Tailed (low-high) *p*-value
AI capabilities → Organizational agility	0.153	0.552	0.399	0.042
AI capabilities → Value definition	0.091	0.532	0.003	0.003
AI capabilities → Value creation	0.052	0.432	0.026	0.026
AI capabilities → Value capture	0.144	0.159	0.015	0.945
Organizational agility → Value definition	0.473	0.405	0.535	0.535
Organizational agility → Value creation	0.495	0.412	0.478	0.478
Organizational agility → Value capture	0.455	0.074	0.073	0.073

Source(s): Authors' elaboration

In addition, we carried out an analysis to explore the relationship between AI capabilities and the level of AI implementation reported by the companies. The primary aim was to determine whether there was a significant difference in AI capabilities between organizations with low and high levels of AI implementation. We employed RStudio, to (1) calculate a composite score for AI capabilities and then (2) compare it between the two groups using a *t*-test (West, 2021). AI capabilities were assessed using a series of indicators (AIC1 to AIC10) measured through a Likert scale. As AI capabilities is a latent variable, we computed a composite score to summarize the overall AI capabilities of each organization. This composite score was derived by applying outer loadings from the prior PLS-SEM model to each indicator. Each indicator was weighted according to its outer loading, ensuring that the composite score reflected the relative importance of each indicator:

$AI\ capabilities\ composite\ score = (AIC1 * outer\ loading_{AIC1}) + (AIC2 * outer\ loading_{AIC2}) + \ldots + (AIC10 * outer\ loading_{AIC10})$ reflected the relative importance of each indicator.

To assess whether AI capabilities differ between organizations with low and high levels of AI implementation, we conducted a Welch's *t*-test (West, 2021). The results showed a statistically significant difference between the two groups ($p < 0.001$), with organizations in the high implementation group reporting significantly stronger AI capabilities. On average, their composite score was 25.32, compared to 19.67 for the low implementation group. This substantial gap suggests that higher levels of AI adoption are associated with a more developed set of AI-related resources and competencies within firms. These findings, represented in

Figure 3, highlight how AI adoption maturity may act as a key enabler for building strategic capabilities, rather than being a mere outcome of digital investment.

6. Discussion

The results obtained provide strong support to all the proposed hypotheses regarding the direct effects. More into detail, the study on PLS-SEM showed that AI capabilities are an important predictor of value definition, value creation and value capture, with stronger effect on value creation ($\beta = 0.309$, $p < 0.001$), followed by value definition ($\beta = 0.274$, $p < 0.001$) and finally by value capture ($\beta = 0.155$, $p < 0.001$), as well as of organizational agility ($\beta = 0.313$, $p < 0.001$), where the β coefficient indicates the strength and direction of the relationship between constructs, with higher values reflecting a stronger impact. Organizational agility is a mediator of the relationship between AI capabilities and the value processes. Indeed, it has a significant positive effect on value creation ($\beta = 0.445$, $p < 0.001$), value definition ($\beta = 0.436$, $p < 0.001$) and value capture ($\beta = 0.617$, $p < 0.001$). The model proved to be robust in explaining the variance of all three stages of the value proposition, value definition (adjusted $R^2 = 34.0\%$), value creation (adjusted $R^2 = 38.0\%$) and value capture (adjusted $R^2 = 46.5\%$) (Hair *et al.*, 2017).

6.1 Implication for theory

This research has several theoretical implications for the emerging literature on AI capabilities. To the best of the authors' knowledge, this is the first study that explores the impact of AI capabilities in PBOs, assessing their effects on project value generation processes. The results confirm the importance of resources underpinning AI capabilities that have been discussed in prior studies (Mikalef and Gupta, 2021; Fosso Wamba, 2022). This theoretical emphasis on AI resource investments underscores that elements such as technical skills, data infrastructure and cross-functional collaboration are foundational to building effective AI capabilities (Mikalef and Gupta, 2021; Abou-Foul *et al.*, 2023). The development of these capabilities requires constant resource allocation, aligning with the RBV (Killen *et al.*, 2012; Lobo and Whyte, 2017). This study supports and extends the theoretical assertion that AI capabilities are not just inherent qualities of an organization but must be cultivated through targeted investments in resources (Abou-Foul *et al.*, 2023; Sahoo *et al.*, 2024). In this sense, our research builds upon and extends the concept of absorptive capacity (Zahra and George,

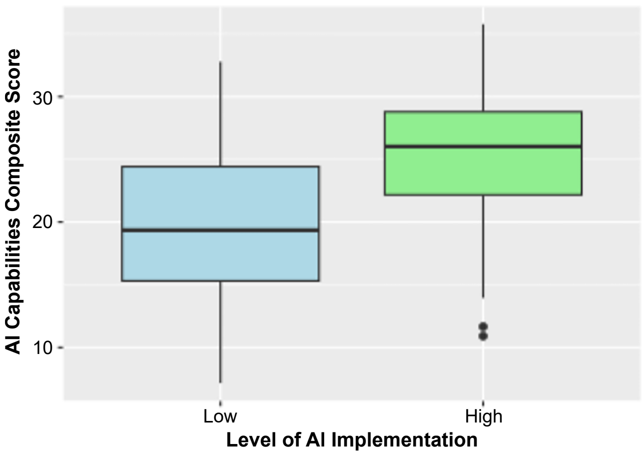

Figure 3. AI capabilities by level of AI implementation. Source: Authors' elaboration

2002) by shifting the focus from mere knowledge recognition and assimilation to the strategic orchestration of technological and organizational resources necessary for generating value at the project level. Further, this study contributes to the literature by empirically demonstrating that AI capabilities influence project value processes both directly and indirectly through organizational agility. Consistent with both Fosso Wamba (2022) and Abou-Foul *et al.* (2023) our findings confirm agility's role as a key mediator that enhances the organization's adaptive capacity and amplifies the impact of AI assimilation. It further reinforces the theoretical importance of organizational agility not just as a supportive factor, but as a crucial mechanism through which AI capabilities realize their full potential in PBOs. This perspective broadens the theoretical understanding of organizational agility's role, already outlined in previous works (Kadenic and Tambo, 2023; Santos *et al.*, 2025) underscoring its direct influence on value definition, creation and capture as a pathway through which AI capabilities deliver maximum value. According to Mikalef and Gupta (2021), AI capabilities alone are insufficient for competitive advantage unless accompanied by complementary resources. Our study supports this view, showing that specific indicators within AI capabilities, like technical skills (AIC6), business skills (AIC8) and adequate resourcing (AIC5) significantly contribute to value definition, creation and capture, suggesting that these capabilities act as VRIN resources when deployed through adaptable processes that allow firms to respond to dynamic market conditions (Ghapanchi *et al.*, 2014; Parker *et al.*, 2015). This aligns with RBV's emphasis on the synergy between resources and organizational processes, highlighting that AI capabilities achieve their full potential only when paired with organizational agility. Furthermore, the variation in AI capabilities' impact across firms with different implementation levels suggests that resources at higher levels of maturity offer a greater advantage. Firms with high AI implementation can better capitalize on their resources, particularly through skilled technical personnel and robust infrastructure, reinforcing RBV's view that competitive advantage is amplified by resource quality and maturity (Barney, 2001; Barney and Arikan, 2005). These findings suggests that organizations that prioritize resource development can significantly enhance their value processes, highlighting the strategic importance of AI within RBV as a high-value organizational asset. Indeed, all the indicators measuring value processes, were found to be almost equally impacted by changes in the respective latent variable, meaning AI capabilities' benefits are proportionally distributed on all aspects of each stage of the value proposition. The MGA results highlight that the relationship between AI capabilities and organizational agility varies by firm size. In larger firms, the stronger impact of AI on value creation suggests that scale enhances the ability to convert AI investments into innovative outcomes. Conversely, smaller firms appear to rely more heavily on organizational agility to generate value, positioning agility as a compensatory mechanism for resource constraints.

6.2 Implication for practice

This study offers empirically grounded insights into how AI capabilities function as value-enabling organizational resources, providing evidence-based guidance on resource prioritization within PBO contexts. Figure 4 reports a synthesis of the implications for practice. First, the findings underscore the importance of investing in targeted AI capabilities, particularly those that have a strong influence on value definition creation and capture. This is especially relevant for project-based organizations and decision-makers seeking to align

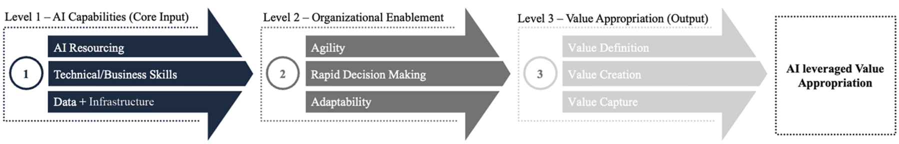

Figure 4. From AI capabilities to value appropriation: a managerial pathway. Source: Authors' elaboration

digital investments with tangible value outcomes. Among the AI capability indicators analyzed, adequate resourcing (AIC5), technical skills (AIC6 and AIC7) and business skills (AIC8), emerged as the ones managers should focus their attention on. The importance of human resources highlighted in our findings does not diminish the importance of other AI-related resources. Rather, it suggests that, while human resources actively drive AI implementation, other resources, such as data access (AIC1) and inter-departmental coordination (AIC9), function more as supportive assets. This implies that, without a structured strategic approach, raw data alone may have limited impact on enhancing value outcomes, thus "making such technically oriented investments alone will most likely not result in substantial performance" (Mikalef and Gupta, 2021).

The study also highlights the importance of organizational agility as a mediator in the relationship between AI capabilities and value processes. This insight is particularly relevant for senior managers and transformation leaders responsible for orchestrating cross-functional collaboration and ensuring that AI investments translate into adaptive and value-generating outcomes. Organizational agility proved to be essential in translating AI capabilities into tangible value outcomes especially in complex, fast-paced environments like the ones PBOs operate in Fosso Wamba (2022). For managers, this means that investments in AI should be accompanied by efforts to build an agile organizational culture, characterized by flexible structures, quick decision-making processes, milestone-driven PM and open communication channels. Additionally, our research provides insights into the value processes most directly impacted by AI capabilities and those more significantly influenced by organizational agility as a mediator. Value creation was found to be the most directly affected by AI capabilities. In contrast, value capture benefits more substantially from the mediating influence of organizational agility. This pattern may indicate that monetizing the benefits of AI requires more than just technical investment – it demands organizational readiness, responsiveness and the ability to translate operational improvements into strategic gains. From an RBV perspective, this underscores the importance of dynamic capabilities in transforming AI resources into sustained economic value, through mechanisms such as service differentiation, knowledge capitalization or bundled digital offerings (Barney, 2001; Almarri and Gardiner, 2014). For example, a firm that uses AI to improve project scheduling and risk detection (value creation) may only realize its full competitive advantage if it also adapts its delivery model, communicates these improvements to clients and leverages them to offer premium or data-enhanced services (value capture). In this sense, agility plays a crucial role in enabling firms to appropriate value from AI capabilities, aligning with RBV's focus on long-term competitive advantage through strategic resource orchestration.

7. Limitation and conclusion

This study provides insights into the role of AI capabilities and organizational agility in driving value within PBOs. Some several limitations should be acknowledged, offering directions for future research. First, the sample size presents a limitation for the MGA implementation. Although MGA provided useful insights, the unbalanced sample size limited the extent to which the analysis could be applied across different groups. Future studies could benefit from larger and more balanced samples to enable a more robust application of MGA, allowing for more structured comparisons across different organizational types, firm sizes, AI maturity levels and even between sector, enhancing the generalizability of findings. Regarding the industries perspective, this study encompassed a broad range of industries, which, while providing a diverse perspective, may have diluted some industry-specific insights. Narrowing the focus to a single industry, such as IT, where AI applications are particularly advanced, could yield interesting insights on how AI capabilities and organizational agility impact value proposition within that sector. Although based on quantitative data, this study involves interpretative reasoning over perceptual constructs. We acknowledge that alternative interpretations of the findings are possible and that our conclusions reflect a specific theoretical framing. Future research may explore different lenses or analytical perspectives to validate or challenge these insights. The use of self-reported data for measuring the indicators introduce the potential for cognitive biases, as responses relied on the subjective judgment of participants. To mitigate such biases and broaden conclusions, future research could incorporate more data collection methods, like case studies or objective performance data, to provide a more reliable dataset (Rosenman *et al.*, 2011). Additionally, the generalizability of the findings may be limited by the geographical composition of the sample, which predominantly includes firms based in Europe. Future studies could expand the geographical scope to test the model across different institutional and cultural contexts.

This study focuses exclusively on organizational agility as a mediator between AI capabilities and value processes. While agility proved to be a significant mediator, other factors may also play essential roles in translating AI capabilities into organizational value. For instance, other internal organizational characteristics, such as absorptive capacity (Ngereja *et al.*, 2024) and a data-driven culture (Fosso Wamba *et al.*, 2024), could serve as mediators, offering further insights into the pathways through which AI impacts value outcomes.

Further, while organizational agility was conceptualized as a dynamic capability, it was modeled as a unidimensional reflective construct due to the limited number of available indicators. Future research could benefit from adopting more granular measurement models that distinguish between agility's underlying components – such as sensing, responding and adapting – as suggested in dynamic capability theory (Teece, 2007). Future studies could build on our findings by integrating key external factors as moderators, reflecting the dynamic nature of the environment in which organizations operate. Potential external moderators include environmental dynamism (Sahoo *et al.*, 2024), technology turbulence (Chatterjee *et al.*, 2023), project complexity (Mata *et al.*, 2023; Serrador and Pinto, 2015), environmental uncertainty (Serrador and Pinto, 2015; Mata *et al.*, 2023) and environmental turbulence (Guo *et al.*, 2023). Exploring these alternative mediators and moderators in future research could provide a comprehensive understanding of how different organizational attributes interact with AI capabilities in PBOs. Future research could build on our framework to explore broader societal implications of AI in projects, including ethical concerns, inclusiveness in AI-supported decision-making and implications for public policy.

Acknowledgments
The authors would like to thank Matilde Belviglieri and Carlotta Calzolari for their support in the first phase of data collection and analysis.

(The Appendix follows overleaf)

Annex 1

Table A1. Items and factor loadings

Construct	Items
AI capabilities	AIC1: We have access to a vast amount of data for analysis, including unstructured or rapidly changing data. This information is organized in data warehouses to facilitate sharing among business units
	AIC2: We have adopted cloud-based services for data processing, enabling the use of APIs (such as Microsoft Cognitive Services, Google Cloud Vision) for carrying out AI and machine learning tasks
	AIC3: We have the processing power required to support AI applications (e.g. distributed computing, GPUs) as well as the necessary network infrastructure (e.g. corporate networks)
	AIC4: We've invested in scalable data storage infrastructures and state-of-the-art end-to-end data security
	AIC5: Our AI initiatives are adequately funded and supported by dedicated teams
	AIC6: Our data scientists (or consultants) are proficient in utilizing AI technologies (machine learning, natural language processing, and deep learning). Additionally, they are capable of managing data analysis, processing, and security
	AIC7: We are hiring experienced data scientists specializing in AI or relying on external IT consultants
	AIC8: Our managers understand the importance of AI initiatives, and they collaborate with data scientists to identify opportunities and risks associated with such projects
	AIC9: Our departments collaborate closely, sharing goals, information, and resources
	AIC10: We are able to anticipate potential organizational resistance to change. We respond in three ways: (1) Communicating the reasons for the change, (2) Engaging in process re-engineering, and (3) Ensuring senior management commitment to new values
Value definition	VD1: We have strong practices in understanding and defining customer requirements (e.g. leveraging existing customer data, surveys, customer journey map, social medias)
	VD2: We conduct thorough market research before launching new products/services
	VD3: We maintain a deep awareness of our competitors' strengths, weaknesses, and actions
	VD4: Compared to our peers, we consider ourselves proactive in contributing to industry discussions and initiatives (e.g. fairs, open innovation, university collaborations)
	VD5: Our projects are differentiated from those of our competitors, offering features that are clearly recognized by the market
Value creation	VCR1: Our clients choose us because we are able to meet planned deadlines more accurately than other companies
	VCR2: Our project teams always have access to the necessary resources to meet their project goals
	VCR3: There is a clear methodology to identify which activities to prioritize along the project
	VCR4: Our company employs systems for monitoring project progress and performance
Value capture	VCA1: The ROI for our projects exceeds the initial projections
	VCA2: We are capable of accurately projecting the project value that we are able to capture and respect such target
	VCA3: Our clients are more satisfied than dissatisfied with the outcomes of our projects
	VCA4: Customers of completed projects engage us again for future projects
	VCA5: Lessons learned from projects are regularly incorporated into the organization's knowledge base and easily accessible to employees

(*continued*)

Table A1. Continued

Construct	Items
Organizational agility	OA1: Our project approach is structured through milestones: the partial results of the project are regularly presented, discussed, and validated by the customer OA2: Along the project delivery, we maintain effective communication with the customer, ensuring transparency and alignment OA3: In case of changes in the project scope, we are able to fastly update the project plan and communicate changes to all stakeholders OA4: In case of changes in the project scope, we are able to fastly analyze new information and make a decision

Source(s): Authors' elaboration

Annex 2

Table A2. Loadings and explained variance (R^2) of first-order dimensions on the second-order construct AI capabilities

Second-order construct	First-order dimension	Loading (standardized)	R^2
AI capabilities	Tangible	0.802	0.643
	Human	0.846	0.716
	Intangible	0.794	0.630

Source(s): Authors' elaboration

References

Abdel-Khalek, H., Hafez, S.M. and Abuel-Magd, Y. (2017), "Financing – scheduling optimization for construction projects by using genetic algorithms", Wales.

Abou-Foul, M., Ruiz-Alba, J.L. and López-Tenorio, P.J. (2023), "The impact of artificial intelligence capabilities on servitization: the moderating role of absorptive capacity-A dynamic capabilities perspective", *Journal of Business Research*, Vol. 157, 113609, doi: 10.1016/j.jbusres.2022.113609.

Acebes, F., Pereda, M., Poza, D., Pajares, J. and Galán, J.M. (2015), "Stochastic earned value analysis using monte carlo simulation and statistical learning techniques", *International Journal of Project Management*, Vol. 33 No. 7, pp. 1597-1609, doi: 10.1016/j.ijproman.2015.06.012.

Aguirre-Urreta, M.I. and Hu, J. (2019), "Detecting common method bias", *ACM SIGMIS - Data Base: The DATABASE for Advances in Information Systems*, Vol. 50 No. 2, pp. 45-70, doi: 10.1145/3330472.3330477.

Akhtar, P., Khan, Z., Tarba, S. and Jayawickrama, U. (2018), "The internet of things, dynamic data and information processing capabilities, and operational agility", *Technological Forecasting and Social Change*, Vol. 136, pp. 307-316, doi: 10.1016/j.techfore.2017.04.023.

Almarri, K. and Gardiner, P. (2014), "Application of resource-based view to project management research: supporters and opponents", *Procedia - Social and Behavioral Sciences*, Vol. 119, pp. 437-445, doi: 10.1016/j.sbspro.2014.03.049.

Alrezaamiri, H., Ebrahimnejad, A. and Motameni, H. (2020), "Parallel multi-objective artificial bee colony algorithm for software requirement optimization", *Requirements Engineering*, Vol. 25 No. 3, pp. 363-380, doi: 10.1007/s00766-020-00328-y.

Ambituuni, A., Azizsafaei, F. and Keegan, A. (2021), "HRM operational models and practices to enable strategic agility in PBOs: managing paradoxical tensions", *Journal of Business Research*, Vol. 133, pp. 170-182, doi: 10.1016/j.jbusres.2021.04.048.

Amit, R. and Schoemaker, P.J.H. (1993), "Strategic assets and organizational rent", *Strategic Management Journal*, Vol. 14 No. 1, pp. 33-46, doi: 10.1002/smj.4250140105.

Anwar, R. and Bashir, M.B. (2023), "A systematic literature review of AI-Based software requirements prioritization techniques", *IEEE Access*, Vol. 11, pp. 143815-143860, doi: 10.1109/ACCESS.2023.3343252.

Arora, C., Grundy, J. and Abdelrazek, M. (2024), "Advancing requirements engineering through generative AI: assessing the role of LLMs", in *Generative AI for Effective Software Development*, Springer, pp. 129-148, doi: 10.1007/978-3-031-55642-5_6.

Baduge, S.K., Thilakarathna, S., Perera, J.S., Arashpour, M., Sharafi, P., Teodosio, B., Shringi, A. and Mendis, P. (2022), "Artificial intelligence and smart vision for building and construction 4.0: machine and deep learning methods and applications", *Automation in Construction*, Vol. 141, 104440, doi: 10.1016/j.autcon.2022.104440.

Barney, J.B. (2001), "Resource-based theories of competitive advantage: a ten-year retrospective on the resource-based view", *Journal of Management*, Vol. 27 No. 6, pp. 643-650, doi: 10.1177/014920630102700602.

Barney, J.B. and Arikan, A.M. (2005), "The resource-based view", in *The Blackwell Handbook of Strategic Management*, Wiley, pp. 123-182, doi: 10.1111/b.9780631218616.2006.00006.x.

Bisi, M. and Goyal, N.K. (2016), "An ANN-PSO-based model to predict fault-prone modules in software", *International Journal of Reliability and Safety*, Vol. 10 No. 3, 243, doi: 10.1504/ijrs.2016.081611.

Bos-de Vos, M., Volker, L. and Wamelink, H. (2019), "Enhancing value capture by managing risks of value slippage in and across projects", *International Journal of Project Management*, Vol. 37 No. 5, pp. 767-783, doi: 10.1016/j.ijproman.2018.12.007.

Bowman, C. and Ambrosini, V. (2000), "Value creation versus value capture: towards a coherent definition of value in strategy", *British Journal of Management*, Vol. 11 No. 1, pp. 1-15, doi: 10.1111/1467-8551.00147.

Bowman, C. and Ambrosini, V. (2010), "How value is created, captured and destroyed", *European Business Review*, Vol. 22 No. 5, pp. 479-495, doi: 10.1108/09555341011068903.

Braojos, J., Benitez, J. and Llorens, J. (2019), "How do social commerce-IT capabilities influence firm performance? Theory and empirical evidence", *Information and Management*, Vol. 56 No. 2, pp. 155-171, doi: 10.1016/j.im.2018.04.006.

Byrum, J. (2022), "AI in financial portfolio management: practical considerations and use cases", pp. 249-270, doi: 10.1007/978-3-030-75729-8_9.

Chan, C.M.L., Teoh, S.Y., Yeow, A. and Pan, G. (2019), "Agility in responding to disruptive digital innovation: case study of an SME", *Information Systems Journal*, Vol. 29 No. 2, pp. 436-455, doi: 10.1111/isj.12215.

Chan, Y.E., Denford, J.S. and Wang, J.J. (2019), "The Co-Evolution of IT, knowledge, and agility in micro and small enterprises", *Journal of Information and Knowledge Management*, Vol. 18 No. 3, p. 1950027, doi: 10.1142/S0219649219500278.

Chang, A., Chih, Y.Y., Chew, E. and Pisarski, A. (2013), "Reconceptualising mega project success in Australian defence: recognising the importance of value co-creation", *International Journal of Project Management*, Vol. 31 No. 8, pp. 1139-1153, doi: 10.1016/j.ijproman.2012.12.005.

Chatterjee, S., Chaudhuri, R., Kamble, S., Gupta, S. and Sivarajah, U. (2023), "Adoption of artificial intelligence and cutting-edge technologies for production system sustainability: a moderator-mediation analysis", *Information Systems Frontiers*, Vol. 25 No. 5, pp. 1779-1794, doi: 10.1007/s10796-022-10317-x.

Cheah, J.H., Amaro, S. and Roldán, J.L. (2023), "Multigroup analysis of more than two groups in PLS-SEM: a review, illustration, and recommendations", *Journal of Business Research*, Vol. 156, 113539, doi: 10.1016/j.jbusres.2022.113539.

Cheng, T. and Yan, R. (2009), "Integrating messy genetic algorithms and simulation to optimize resource utilization", *Computer-Aided Civil and Infrastructure Engineering*, Vol. 24 No. 6, pp. 401-415, doi: 10.1111/j.1467-8667.2008.00588.x.

Cheng, M.Y., Tsai, H.C. and Sudjono, E. (2010), "Conceptual cost estimates using evolutionary fuzzy hybrid neural network for projects in construction industry", *Expert Systems with Applications*, Vol. 37 No. 6, pp. 4224-4231, doi: 10.1016/j.eswa.2009.11.080.

Cheng, M.Y., Hoang, N.D. and Wu, Y.W. (2015), "Cash flow prediction for construction project using a novel adaptive time-dependent least squares support vector machine inference model", *Journal of Civil Engineering and Management*, Vol. 21 No. 6, pp. 679-688, doi: 10.3846/13923730.2014.893906.

Cheng, M.-Y., Chang, Y.-H. and Korir, D. (2019), "Novel approach to estimating schedule to completion in construction projects using sequence and nonsequence learning", *Journal of Construction Engineering and Management*, Vol. 145 No. 11, pp. 1-17, doi: 10.1061/(asce)co.1943-7862.0001697.

Chesbrough, H. (2007), "Business model innovation: it's not just about technology anymore", *Strategy and Leadership*, Vol. 35 No. 6, pp. 12-17, doi: 10.1108/10878570710833714.

Chesbrough, H. and Rosenbloom, R.S. (2002), "The role of the business model in capturing value from innovation: evidence from Xerox corporation's technology spin-off companies".

Ciric Lalic, D., Lalic, B., Delić, M., Gracanin, D. and Stefanovic, D. (2022), "How project management approach impact project success? From traditional to agile", *International Journal of Managing Projects in Business*, Vol. 15 No. 3, pp. 494-521, doi: 10.1108/IJMPB-04-2021-0108.

Cohen, J. (2013), *Statistical Power Analysis for the Behavioral Sciences*, Routledge, doi: 10.4324/9780203771587.

Conforto, E.C., Amaral, D.C., da Silva, S.L., Di Felippo, A. and Kamikawachi, D.S.L. (2016), "The agility construct on project management theory", *International Journal of Project Management*, Vol. 34 No. 4, pp. 660-674, doi: 10.1016/j.ijproman.2016.01.007.

Costantino, F., Di, G. and Nonino, F. (2015), "Project selection in project portfolio management : an arti fi cial neural network model based on critical success factors", *Journal of the Pakistan Medical Association*, Vol. 33 No. 8, pp. 1744-1754, doi: 10.1016/j.ijproman.2015.07.003.

Dam, H.K., Tran, T., Grundy, J., Ghose, A. and Kamei, Y. (2019), "Towards effective AI-Powered agile project management", *2019 IEEE/ACM 41st International Conference on Software Engineering: New Ideas and Emerging Results (ICSE-NIER)*, IEEE, pp. 41-44, doi: 10.1109/ICSE-NIER.2019.00019.

El-Abbasy, M.S., Elazouni, A. and Zayed, T. (2020), "Finance-based scheduling multi-objective optimization: benchmarking of evolutionary algorithms", *Automation in Construction*, Vol. 120, 103392, doi: 10.1016/j.autcon.2020.103392.

Elnabwy, M.T., Khalaf, D., Mlybari, E.A. and Elbeltagi, E. (2024), "An integrated machine learning approach for evaluating critical success factors influencing project portfolio management adoption in the construction industry", *Engineering Construction and Architectural Management*, Vol. 367, 122018, doi: 10.1108/ECAM-05-2024-0537.

Enholm, I.M., Enholm, E. and Mikalef, P. (2022), "Artificial intelligence and business value: a literature review", *Information Systems Frontiers*, Vol. 24 No. 1, pp. 1709-1734, doi: 10.1007/s10796-021-10186-w.

Faghihi, V., Nejat, A., Reinschmidt, K.F. and Kang, J.H. (2015), "Automation in construction scheduling : a review of the literature", *International Journal of Andvanced Manufacturing Technologies*, Vol. 81 Nos 9-12, pp. 1845-1856, doi: 10.1007/s00170-015-7339-0.

Faul, F., Erdfelder, E., Buchner, A. and Lang, A.G. (2009), "Statistical power analyses using G*Power 3.1: tests for correlation and regression analyses", *Behavior Research Methods*, Vol. 41 No. 4, pp. 1149-1160, doi: 10.3758/BRM.41.4.1149.

Ferraris, A., Degbey, W.Y., Singh, S.K., Bresciani, S., Castellano, S., Fiano, F. and Couturier, J. (2022), "Microfoundations of strategic agility in emerging markets: empirical evidence of Italian MNEs in India", *Journal of World Business*, Vol. 57 No. 2, 101272, doi: 10.1016/j.jwb.2021.101272.

Flyvbjerg, B., Budzier, A., Chun-kit, Lau, R., Agard, K., Agard, K. and Leed, A. (2022), "AI in action: how the Hong Kong development bureau built the pss — an early-warning-sign system for public works projects", *SSRN*, pp. 1-28.

Fosso Wamba, S. (2022), "Impact of artificial intelligence assimilation on firm performance: the mediating effects of organizational agility and customer agility", *International Journal of Information Management*, Vol. 67, 102544, doi: 10.1016/j.ijinfomgt.2022.102544.

Fosso Wamba, S., Queiroz, M.M. and Trinchera, L. (2024), "The role of artificial intelligence-enabled dynamic capability on environmental performance: the mediation effect of a data-driven culture in France and the USA", *International Journal of Production Economics*, Vol. 268, 109131, doi: 10.1016/j.ijpe.2023.109131.

Frank, S., Bod, R. and Christiansen, M.H. (2012), "How hierarchical is language use?", *Proceedings of the Royal Society B: Biological Sciences*, Vol. 279 No. 1747, pp. 4522-4531, doi: 10.1098/rspb.2012.1741.

Fridgeirsson, T.V., Ingason, H.T., Jonasson, H.I. and Jonsdottir, H. (2021), "An authoritative study on the near future effect of artificial intelligence on project management knowledge areas", *Sustainability*, Vol. 13 No. 4, pp. 1-20, doi: 10.3390/su13042345.

Fuller, C.M., Simmering, M.J., Atinc, G., Atinc, Y. and Babin, B.J. (2016), "Common methods variance detection in business research", *Journal of Business Research*, Vol. 69 No. 8, pp. 3192-3198, doi: 10.1016/j.jbusres.2015.12.008.

Gama, F. and Magistretti, S. (2023), "Artificial intelligence in innovation management: a review of innovation capabilities and a taxonomy of AI applications", *Journal of Product Innovation Management*, Vol. 42 No. 1, pp. 76-111, doi: 10.1111/jpim.12698.

Ghapanchi, A.H., Wohlin, C. and Aurum, A. (2014), "Resources contributing to gaining competitive advantage for open source software projects: an application of resource-based theory", *International Journal of Project Management*, Vol. 32 No. 1, pp. 139-152, doi: 10.1016/j.ijproman.2013.03.002.

Ghorbani, S. and Rabbani, M. (2009), "A new multi-objective algorithm for a project selection problem", *Advances in Engineering Software*, Vol. 40 No. 1, pp. 9-14, doi: 10.1016/j.advengsoft.2008.03.002.

Gligor, D.M., Esmark, C.L. and Holcomb, M.C. (2015), "Performance outcomes of supply chain agility: when should you be agile?", *Journal of Operations Management*, Vols 33-34 No. 1, pp. 71-82, doi: 10.1016/j.jom.2014.10.008.

Guo, R., Yin, H. and Liu, X. (2023), "Coopetition, organizational agility, and innovation performance in digital new ventures", *Industrial Marketing Management*, Vol. 111, pp. 143-157, doi: 10.1016/j.indmarman.2023.04.003.

Haddadi, A., Johansen, A. and Bjørberg, S. (2017), "Best value approach (BVA): enhancing value creation in construction projects", *Business Systems Research*, Vol. 8 No. 2, pp. 84-100, doi: 10.1515/bsrj-2017-0018.

Haenlein, M. and Kaplan, A. (2019), "A brief history of artificial intelligence: on the past, present, and future of artificial intelligence", *California Management Review*, Vol. 61 No. 4, pp. 5-14, doi: 10.1177/0008125619864925.

HAI Stanford (2024), *Artificial Intelligence Index Report 2024*.

Hair, H. and Ringle (2021), *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R*.

Hair, J.F., Hult, T., Ringle, C. and Sarstedt, M. (2017), *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, Sage.

Hair, J.M.L.M., Matthews, R.L. and Sarstedt, M. (2017), "PLS-SEM or CB-SEM: updated guidelines on which method to use", *International Journal of Multivariate Data Analysis*, Vol. 1 No. 2, p. 107, doi: 10.1504/IJMDA.2017.087624.

Hair, J.F., Risher, J.J., Sarstedt, M. and Ringle, C.M. (2019), "When to use and how to report the results of PLS-SEM", *European Business Review*, Vol. 31 No. 1, pp. 2-24, doi: 10.1108/EBR-11-2018-0203.

Harraf, A., Wanasika, I., Tate, K. and Talbott, K. (2015), “Organizational agility”, *Journal of Applied Business Research*, Vol. 31 No. 2, p. 675, doi: 10.19030/jabr.v31i2.9160.

Helfat, C.E. and Peteraf, M.A. (2015), “Managerial cognitive capabilities and the microfoundations of dynamic capabilities”, *Strategic Management Journal*, Vol. 36 No. 6, pp. 831-850, doi: 10.1002/smj.2247.

Henseler, J., Hubona, G. and Ray, P.A. (2016), “Using PLS path modeling in new technology research: updated guidelines”, *Industrial Management and Data Systems*, Vol. 116 No. 1, pp. 2-20, doi: 10.1108/IMDS-09-2015-0382.

Holzmann, V., Zitter, D. and Peshkess, S. (2022), “The expectations of project managers from Arti fi cial intelligence: a Delphi study” Vol. 53 No. 5, pp. 438-455, doi: 10.1177/87569728211061779.

Hossain, M.A. and Chua, D.K.H. (2014), “Overlapping design and construction activities and an optimization approach to minimize rework”, *International Journal of Project Management*, Vol. 32 No. 6, pp. 983-994, doi: 10.1016/j.ijproman.2013.10.019.

Hujainah, F., Binti Abu Bakar, R., Nasser, A.B., Al-haimi, B. and Zamli, K.Z. (2021), “SRPTackle: a semi-automated requirements prioritisation technique for scalable requirements of software system projects”, *Information and Software Technology*, Vol. 131, 106501, doi: 10.1016/j.infsof.2020.106501.

Inan, T., Narbaev, T. and Hazir, Ö. (2022), “A machine learning study to enhance project cost forecasting”, in *IFAC-PapersOnLine*, Elsevier B.V., pp. 3286-3291, doi: 10.1016/j.ifacol.2022.10.127.

Jacobides, M.G. and Winter, S.G. (2005), “The co-evolution of capabilities and transaction costs: explaining the institutional structure of production”, *Strategic Management Journal*, Vol. 26 No. 5, pp. 395-413, doi: 10.1002/smj.460.

Jafarzadeh, H., Akbari, P. and Abedin, B. (2018), “A methodology for project portfolio selection under criteria prioritisation, uncertainty and projects interdependency – combination of fuzzy QFD and DEA”, *Expert Systems with Applications*, Vol. 110, pp. 237-249, doi: 10.1016/j.eswa.2018.05.028.

Kadenic, M.D. and Tambo, T. (2023), “Resilience of operating models: exploring the potential of agile project management as enabler”, *International Journal of Managing Projects in Business*, Vol. 16 No. 3, pp. 521-542, doi: 10.1108/IJMPB-05-2022-0122.

Kankaraš, M. and Capecchi, S. (2024), “Neither agree nor disagree: use and misuse of the neutral response category in Likert-type scales”, *Metron*, Vol. 83 No. 1, pp. 111-140, doi: 10.1007/s40300-024-00276-5.

Khakzad, N., Khan, F., Amyotte, P. and Cozzani, V. (2013), “Domino effect analysis using Bayesian networks”, *Risk Analysis*, Vol. 33 No. 2, pp. 292-306, doi: 10.1111/j.1539-6924.2012.01854.x.

Kiani, A. (2024), “Artificial intelligence in entrepreneurial project management: a review, framework and research agenda”, *International Journal of Managing Projects in Business*, doi: 10.1108/IJMPB-03-2024-0068.

Killen, C.P., Jugdev, K., Drouin, N. and Petit, Y. (2012), “Advancing project and portfolio management research: applying strategic management theories”, *International Journal of Project Management*, Vol. 30 No. 5, pp. 525-538, doi: 10.1016/j.ijproman.2011.12.004.

Kock, N. (2015), “Common method bias in PLS-SEM”, *International Journal of E-Collaboration*, Vol. 11 No. 4, pp. 1-10, doi: 10.4018/ijec.2015100101.

Korotkova, N., Lillieskōld, J. and Hetemi, E. (2024), “Pursuing openness in the digital age: insights from client–contractor knowledge collaboration at the project front end”, *International Journal of Project Management*, Vol. 42 No. 1, 102564, doi: 10.1016/j.ijproman.2024.102564.

Krakowski, S., Luger, J. and Raisch, S. (2023), “Artificial intelligence and the changing sources of competitive advantage”, *Strategic Management Journal*, Vol. 44 No. 6, pp. 1425-1452, doi: 10.1002/smj.3387.

Laursen, M. and Svejvig, P. (2016), “Taking stock of project value creation: a structured literature review with future directions for research and practice”, *International Journal of Project Management*, Vol. 34 No. 4, pp. 736-747, doi: 10.1016/j.ijproman.2015.06.007.

Lee, O.-K., Daniel, Lim, K.H. and Wei, K.K. (2015), “How does IT ambidexterity impact organizational agility?”, *Information Systems Research*, Vol. 26 No. 2, pp. 398-417, doi: 10.1287/isre.2015.0577.

Lehtinen, J., Peltokorpi, A. and Artto, K. (2019), “Megaprojects as organizational platforms and technology platforms for value creation”, *International Journal of Project Management*, Vol. 37 No. 1, pp. 43-58, doi: 10.1016/j.ijproman.2018.10.001.

Lepak, D.P., Smith, K.G. and Taylor, M.S. (2007), “Introduction to special topic forum value creation and value capture: a multilevel perspective”.

Li, J. and Zuo, J. (2024), “Cost-benefit analysis and ROI prediction for smart renovation of sports stadiums”, *Applied Mathematics and Nonlinear Sciences*, Vol. 9 No. 1, 20242405, doi: 10.2478/amns-2024-2405.

Libai, B., Bart, Y., Gensler, S., Hofacker, C.F., Kaplan, A., Kötterheinrich, K. and Kroll, E.B. (2020), “Brave new world? On AI and the management of customer relationships”, *Journal of Interactive Marketing*, Vol. 51 No. 1, pp. 44-56, doi: 10.1016/j.intmar.2020.04.002.

Lobo, S. and Whyte, J. (2017), “Aligning and reconciling: building project capabilities for digital delivery”, *Research Policy*, Vol. 46 No. 1, pp. 93-107, doi: 10.1016/j.respol.2016.10.005.

Mackenzie, S.B., Podsakoff, P.M. and Podsakoff, N.P. (2011), “Construct measurement and validation procedures in MIS and behavioral research: integrating new and existing techniques”, *Source: MIS Quarterly*.

Mainga, W. (2017), “Examining project learning, project management competencies, and project efficiency in project-based firms (PBFs)”, *International Journal of Managing Projects in Business*, Vol. 10 No. 3, pp. 454-504, doi: 10.1108/IJMPB-04-2016-0035.

Makadok, R. (2001), “Toward a synthesis of the resource-based and dynamic-capability views of rent creation”, *Strategic Management Journal*, Vol. 22 No. 5, pp. 387-401, doi: 10.1002/smj.158.

Malik, A., De Silva, M.T., Budhwar, P. and Srikanth, N. (2021), “Elevating talents’ experience through innovative artificial intelligence-mediated knowledge sharing: evidence from an IT-multinational enterprise”, *Journal of International Management*, Vol. 27 No. 4, 100871, doi: 10.1016/j.intman.2021.100871.

Manurung, A.H. and Kurniawan, R. (2022), “Organizational agility: do agile project management and networking capability require market orientation?”, *International Journal of Managing Projects in Business*, Vol. 15 No. 1, pp. 1-35, doi: 10.1108/IJMPB-10-2020-0310.

Mancini, M., Mariani, C. and Manfredi, C.M. (2023), “Nuclear decommissioning risk management adopting a comprehensive artificial intelligence framework: an applied case in an Italian site”, *Progress in Nuclear Energy*, Vol. 158 February, 104589, doi: 10.1016/j.pnucene.2023.104589.

Mariani, C. and Mancini, M. (2023), “Selection of projects’ primary and secondary mitigation actions through optimization methods in nuclear decommissioning projects”, *Nuclear Engineering and Design*, Vol. 407, 112284, doi: 10.1016/j.nucengdes.2023.112284.

Mariani, C., Navrotska, Y. and Mancini, M. (2023), “Unsupervised machine learning for project stakeholder classification: benefits and limitations”, *Project Leadership and Society*, Vol. 4, 100093, doi: 10.1016/j.plas.2023.100093.

Mariani, C., Caccialanza, A., Bugarčić, M., Slavkovic, M. and Mancini, M. (2025a), “Enhancing project-based organization performance through ESG practices: the role of organizational agility”, *Management Decision*, doi: 10.1108/MD-04-2024-0967.

Mariani, C., Cellerino, F., Araya Aliaga, E.H., Atencio, E. and Mancini, M. (2025b), “The C-BA method: enhancing megaproject forecasting through the “Fifth Hand” principle”, *International Journal of Managing Projects in Business*, Vol. 18 No. 8, pp. 50-78, doi: 10.1108/IJMPB-11-2024-0281.

Marr, B. (2018), *What is AI?*, available at: https://bernardmarr.com/what-is-ai/

Martinsuo, M. and Hoverfält, P. (2018), “Change program management: toward a capability for managing value-oriented, integrated multi-project change in its context”, *International Journal of Project Management*, Vol. 36 No. 1, pp. 134-146, doi: 10.1016/j.ijproman.2017.04.018.

Martinsuo, M., Klakegg, O.J. and van Marrewijk, A. (2019), "Editorial: delivering value in projects and project-based business", *International Journal of Project Management*, Vol. 37 No. 5, pp. 631-635, doi: 10.1016/j.ijproman.2019.01.011.

Mata, M.N., Martins, J.M. and Inácio, P.L. (2023), "Impact of absorptive capacity on project success through mediating role of strategic agility: project complexity as a moderator", *Journal of Innovation and Knowledge*, Vol. 8 No. 1, 100327, doi: 10.1016/j.jik.2023.100327.

McKinsey (2024), *The State of AI in Early 2024: Gen AI Adoption Spikes and Starts to Generate Value*.

McKnight, P.E. and Najab, J. (2010), "Mann-whitney U test", in *The Corsini Encyclopedia of Psychology*, Wiley, p. 1, doi: 10.1002/9780470479216.corpsy0524.

Mikalef, P. and Gupta, M. (2021), "Artificial intelligence capability: conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance", *Information and Management*, Vol. 58 No. 3, 103434, doi: 10.1016/j.im.2021.103434.

MIT Sloan (2024), *Leading with AI: Insights for Success in ai-driven Organizations*.

Miterev, M., Jerbrant, A. and Feldmann, A. (2020), "Exploring the alignment between organization designs and value processes over the program lifecycle", *International Journal of Project Management*, Vol. 38 No. 2, pp. 112-123, doi: 10.1016/j.ijproman.2019.12.003.

Mol, J.M., Wijnberg, N.M. and Carroll, C. (2005), "Value chain envy: explaining new entry and vertical integration in popular music", *Journal of Management Studies*, Vol. 42 No. 2, pp. 251-276, doi: 10.1111/j.1467-6486.2005.00496.x.

Momeni, H., Motameni, H. and Larimi, M. (2014), "A neuro-fuzzy based approach to software quality requirements prioritization", *International Journal of Applied Information Systems (IJAIS)*, Vol. 7 No. 7, pp. 15-20, doi: 10.5120/ijais14-451207, available at: www.ijais.org

Moradi, S., Kähkönen, K. and Aaltonen, K. (2020), "Comparison of research and industry views on project managers' competencies", *International Journal of Managing Projects in Business*, Vol. 13 No. 3, pp. 543-572, doi: 10.1108/IJMPB-04-2019-0085.

Myszkowski, P.B., Skowroński, M.E., Olech, Ł.P. and Oślizło, K. (2015), "Hybrid ant colony optimization in solving multi-skill resource-constrained project scheduling problem", *Soft Computing*, Vol. 19 No. 12, pp. 3599-3619, doi: 10.1007/s00500-014-1455-x.

Naz, H., Motla, Y.H., Asghar, S., Abbas, M.A. and Khatoon, A. (2013), "Effective usage of AI technique for requirement change management practices", *IEEE*, pp. 121-125, doi: 10.1109/csit.2013.6588769.

Ngereja, B.J., Hussein, B. and Wolff, C. (2024), "Exploring the impact of absorptive capacity to navigate the challenges of uncertainty in digitalization projects", *International Journal of Managing Projects in Business*, Vol. 17 Nos 4/5, pp. 618-643, doi: 10.1108/IJMPB-01-2024-0013.

Papadonikolaki, E., Krystallis, I. and Morgan, B. (2022), "Digital technologies in built environment projects: review and future directions", *Project Management Journal*, Vol. 53 No. 5, pp. 501-519, doi: 10.1177/87569728211070225.

Parker, D.W., Parsons, N. and Isharyanto, F. (2015), "Inclusion of strategic management theories to project management", *International Journal of Managing Projects in Business*, Vol. 8 No. 3, pp. 552-573, doi: 10.1108/IJMPB-11-2014-0079.

Peng, J. and Liu, X. (2022), "Labor resource allocation under extremely short construction period based on the inverse optimization method", *Engineering Construction and Architectural Management*, Vol. 1 No. 3, pp. 1254-1271, doi: 10.1108/ECAM-06-2022-0604.

Polkowski, Z., Vora, J., Tanwar, S., Tyagi, S., Singh, P.K. and Singh, Y. (2019), "Machine learning-based software effort estimation : an analysis", *IEEE*, pp. 1-6, doi: 10.1109/ecai46879.2019.9042031.

Ramzan, M., Arfan Jaffar, M. and Shahid, A.A. (2011), "Value based intelligent requirement prioritization (VIRP): expert driven fuzzy logic based prioritization technique", *International Journal of Innovative Computing, Information and Control*, Vol. 7 No. 3, pp. 1017-1038.

Regona, M., Yigitcanlar, T., Hon, C. and Teo, M. (2024), "Artificial intelligence and sustainable development goals: systematic literature review of the construction industry", *Sustainable Cities and Society*, Vol. 108, 105499, doi: 10.1016/j.scs.2024.105499.

Relich, M. and Pawlewski, P. (2017), "A fuzzy weighted average approach for selecting portfolio of new product development projects", *Neurocomputing*, Vol. 231, pp. 19-27, doi: 10.1016/j.neucom.2016.05.104.

Rosenman, R., Tennekoon, V. and Hill, L.G. (2011), "Measuring bias in self-reported data", *International Journal of Behavioural and Healthcare Research*, Vol. 2 No. 4, p. 320, doi: 10.1504/IJBHR.2011.043414.

Sahoo, S., Kumar, S., Donthu, N. and Singh, A.K. (2024), "Artificial intelligence capabilities, open innovation, and business performance – empirical insights from multinational B2B companies", *Industrial Marketing Management*, Vol. 117, pp. 28-41, doi: 10.1016/j.indmarman.2023.12.008.

Santos, P.de O., Alves, J.L. and Carvalho, M.M.de (2025), "Facing barriers to unlock large-scale agile benefits: exploring the mediating role of organizational readiness", *International Journal of Managing Projects in Business*, Vol. 18 No. 1, pp. 26-52, doi: 10.1108/IJMPB-02-2024-0044.

Sarstedt, M., Ringle, C.M. and Hair, J.F. (2014), "PLS-SEM: looking back and moving forward", *Long Range Planning*, Vol. 47 No. 3, pp. 132-137, doi: 10.1016/j.lrp.2014.02.008.

Sarstedt, M., Hair, J.F., Jr, Cheah, J.H., Becker, J.M. and Ringle, C.M. (2019), "How to specify, estimate, and validate higher-order constructs in PLS-SEM", *Australasian Marketing Journal*, Vol. 27 No. 3, pp. 197-211, doi: 10.1016/j.ausmj.2019.05.003.

Schmidt, R., Zimmermann, R., Möhring, A. and Keller, M. (2020), "Value creation in connectionist artificial intelligence-a research agenda", available at: https://aisel.aisnet.org/amcis2020/ai_semantic_for_intelligent_info_systems/ai_semantic_for_intelligent_info_systems/14

Serrador, P. and Pinto, J.K. (2015), "Does agile work? - a quantitative analysis of agile project success", *International Journal of Project Management*, Vol. 33 No. 5, pp. 1040-1051, doi: 10.1016/j.ijproman.2015.01.006.

Shams, R., Vrontis, D., Belyaeva, Z., Ferraris, A. and Czinkota, M.R. (2021), "Strategic agility in international business: a conceptual framework for "agile" multinationals", *Journal of International Management*, Vol. 27 No. 1, 100737, doi: 10.1016/j.intman.2020.100737.

Sireci, S.G. (1998), "The construct of content validity", *Social Indicators Research*, Vol. 45 Nos 1/3, pp. 83-117, doi: 10.1023/A:1006985528729.

Sirmon, D.G., Hitt, M.A. and Ireland, R.D. (2007), "Managing firm resources in dynamic environments to create value: looking inside the black box", *Academy of Management Review*, Vol. 32 No. 1, pp. 273-292, doi: 10.5465/amr.2007.23466005.

Sjödin, D., Parida, V., Jovanovic, M. and Visnjic, I. (2020), "Value creation and value capture alignment in business model innovation: a process view on outcome-based business models", *Journal of Product Innovation Management*, Vol. 37 No. 2, pp. 158-183, doi: 10.1111/jpim.12516.

Sjödin, D., Parida, V., Palmié, M. and Wincent, J. (2021), "How AI capabilities enable business model innovation: scaling AI through co-evolutionary processes and feedback loops", *Journal of Business Research*, Vol. 134, pp. 574-587, doi: 10.1016/j.jbusres.2021.05.009.

Svejvig, P., Geraldi, J. and Grex, S. (2019), "Accelerating time to impact: deconstructing practices to achieve project value", *International Journal of Project Management*, Vol. 37 No. 5, pp. 784-801, doi: 10.1016/j.ijproman.2018.12.003.

Taherdoost, H. and Madanchian, M. (2023), "Artificial intelligence and knowledge management: impacts, benefits, and implementation", *Computers*, Vol. 12 No. 4, p. 72, MDPI, doi: 10.3390/computers12040072.

Tallon, P.P., Queiroz, M., Coltman, T. and Sharma, R. (2019), "Information technology and the search for organizational agility: a systematic review with future research possibilities", *The Journal of Strategic Information Systems*, Vol. 28 No. 2, pp. 218-237, doi: 10.1016/j.jsis.2018.12.002.

Taylan, O., Bafail, A.O., Abdulaal, R.M. and Kabli, M.R. (2014), "Construction projects selection and risk assessment by fuzzy AHP and fuzzy TOPSIS methodologies", *Applied Soft Computing Journal*, Vol. 17, pp. 105-116, doi: 10.1016/j.asoc.2014.01.003.

Teece, D.J. (2007), "Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance", *Strategic Management Journal*, Vol. 28 No. 13, pp. 1319-1350, doi: 10.1002/smj.640.

Teece, D.J. (2018), "Profiting from innovation in the digital economy: enabling technologies, standards, and licensing models in the wireless world", *Research Policy*, Vol. 47 No. 8, pp. 1367-1387, doi: 10.1016/j.respol.2017.01.015.

Trach, R., Trach, Y. and Lendo-siwicka, M. (2021), "Using ann to predict the impact of communication factors on the rework cost in construction projects", *Energies*, Vol. 14 No. 14, p. 4376, doi: 10.3390/en14144376.

Trost, A. (2020), "Human resources strategies: balancing stability and agility in times of digitization future of business and finance", available at: http://www.springer.com/series/16360

Volkmar, G., Fischer, P.M. and Reinecke, S. (2022), "Artificial intelligence and machine learning: exploring drivers, barriers, and future developments in marketing management", *Journal of Business Research*, Vol. 149 June, pp. 599-614, doi: 10.1016/j.jbusres.2022.04.007.

Walker, D. and Lloyd-Walker, B. (2019), "The future of the management of projects in the 2030s", *International Journal of Managing Projects in Business*, Vol. 12 No. 2, pp. 242-266, doi: 10.1108/IJMPB-02-2018-0034.

Wamba-Taguimdje, S.L., Fosso Wamba, S., Kala Kamdjoug, J.R. and Tchatchouang Wanko, C.E. (2020), "Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects", *Business Process Management Journal*, Vol. 26 No. 7, pp. 1893-1924, doi: 10.1108/BPMJ-10-2019-0411.

Wang, Y.-R., Yu, C.-Y. and Chan, H.-H. (2012), "Predicting construction cost and schedule success using artificial neural networks ensemble and support vector machines classification models", *International Journal of Project Management*, Vol. 30 No. 4, pp. 470-478, doi: 10.1016/j.ijproman.2011.09.002.

Wauters, M. and Vanhoucke, M. (2014), "Support vector machine regression for project control forecasting", *Automation in Construction*, Vol. 47, pp. 92-106, doi: 10.1016/j.autcon.2014.07.014.

Werder, K., Richter, J., Hennel, P., Dreesen, T., Fischer, M. and Weingarth, J. (2021), "A three-pronged view on organizational agility", *IT Professional*, Vol. 23 No. 2, pp. 89-95, doi: 10.1109/MITP.2020.3016488.

West, R.M. (2021), "Best practice in statistics: use the welch *t* -test when testing the difference between two groups", *Annals of Clinical Biochemistry: International Journal of Laboratory Medicine*, Vol. 58 No. 4, pp. 267-269, doi: 10.1177/0004563221992088.

Yan, H., Yang, N., Peng, Y. and Ren, Y. (2020), "Data mining in the construction industry: present status, opportunities, and future trends", *Automation in Construction*, Vol. 119, 103331, doi: 10.1016/j.autcon.2020.103331.

Zahra, S.A. and George, G. (2002), "Absorptive capacity: a review, reconceptualization, and extension", *Academy of Management Review*, Vol. 27 No. 2, pp. 185-203, doi: 10.5465/amr.2002.6587995.

Zhang, Y.F. (2024), "Too little or too much transparency? Influencing accountability in project management through the practices of using digital technologies", *International Journal of Project Management*, Vol. 42 No. 6, 102636, doi: 10.1016/j.ijproman.2024.102636.

Zhao, C., Zhou, Y. and Lai, X. (2022), "An integrated framework with evolutionary algorithm for multi-scenario multi-objective optimization problems", *Information Sciences*, Vol. 600, pp. 342-361, doi: 10.1016/j.ins.2022.03.093.

Zott, C. and Amit, R. (2010), "Business model design: an activity system perspective", *Long Range Planning*, Vol. 43 Nos 2-3, pp. 216-226, doi: 10.1016/j.lrp.2009.07.004.

Corresponding author
Costanza Mariani can be contacted at: costanza.mariani@polimi.it