CONCEPTUAL FRAMEWORK TO GUIDE THE APPLICATION OF ARTIFICIAL INTELLIGENCE IN PROJECT MANAGEMENT DECISION MAKING

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Abstract

Projects continue to fail despite technological advancements, with poor decision-making being a primary contributing factor. With the growing interest in Artificial Intelligence (AI) in project management (PM) and decision-making, AI could improve decision-making and project performance. However, to implement AI for this purpose, limited comprehensive guidelines and frameworks exist to assist project managers in identifying where to begin, which critical factors to consider, what changes or developments are necessary, and the specific expertise required. Therefore, this study explores the critical factors for implementing AI in project decision-making through a mixed-methods approach. Firstly, a semi-structured focus group interview was conducted with selected individuals from a project-based engineering firm. The thematic analysis of the qualitative data identified limitations in project success and decision-making, as well as implementation considerations for AI in project decision-making. Secondly, quantitative data was gathered using an online survey and analysed using descriptive statistics to rank the importance of the seven identified success groups and their factors. A conceptual framework was developed considering the importance of the seven success groups and their factors. This framework addresses the shortcomings of an existing model to guide the successful implementation of AI in PM to support and improve project decision-making and performance.

Keywords: Artificial intelligence, Decision-making, Implementation factors, Project management, Project performance.

1 Introduction

Many companies heavily rely on the success of projects for a competitive advantage. Even though efforts are made to advance technically, many projects still fail regarding performance metrics (i.e., meeting deadlines, staying within budget, staying in scope, delivering quality, and meeting the client's expectations). The pressure to deliver projects in even shorter timeframes and at reduced costs, with the challenge that projects are becoming more technically complex (van Besouw and Bond-Barnard, 2021), further impacts the successful execution of projects. Many of the current project management (PM) practices still heavily rely on human input and manual data capturing (van Besouw and Bond-Barnard, 2021, Mishra et al., 2022).

Decision-making is integral to project success (Barcaui and Monat, 2023). Project decision-making (PDM) is the process of making decisions that affect the outcome of a project. For project managers and decision-makers to make sound decisions, high-quality information is required (i.e., poor information quality leads to poor decision-making) (Caniëls and Bakens, 2012). Effective decision-making is usually limited by three elements: incomplete and inaccurate information, cognitive limitations when interpreting data/information, and the limited time available to make the decision (Secundo et al., 2022). However, van Besouw and Bond-Barnard (2021) highlighted the potential of applying Artificial Intelligence (AI) in Project Management Information Systems (PMIS), which can analyse vast amounts of project data to identify patterns and anomalies and communicate the information to project stakeholders, providing insight to make actionable decisions. Moreover, Hashfi and Raharjo (2023) highlighted that AI in PM could improve project success rates and outcomes. However, when implementing AI in an organization to aid PDM, there is a lack of comprehensive guidelines and frameworks to assist project managers in identifying where to begin, which critical factors to consider, what changes or developments are necessary, and the specific expertise required.

Therefore, to address the research problem, the research objective is to develop a conceptual framework for project managers to guide the potential implementation of AI as a tool for PDM. The study is structured to answer the following research questions to achieve the objective:

1. What factors should be considered to apply AI in PDM?
2. Are certain factors more or less important than others to consider when applying AI in PDM?

2 Literature Review

2.1 Project management

By definition, no two projects are alike; although they may be similar, they can vary in multiple ways (e.g. cost, scope, scale, constraints, theme, etc.), which poses a challenge to formulate best practices. However, the Project Management Institute (PMI) developed "A Guide to the Project Management Body of Knowledge" (PMBOK), which has been the standard for best practices and approaches regarding project processes, life cycle, and competence areas. PMBOK defines PM as "the application of knowledge, skills, tools, and techniques to project activities to meet requirements. PM refers to guiding the project work to deliver the intended outcomes. Project teams can achieve the outcome using a broad range of approaches (e.g., predictive, hybrid, and adaptive)" (PMBOK® Guide, 2021).

Many companies heavily rely on the success of projects for a competitive advantage. Project success and performance include both efficiency objectives (i.e. time, cost, and quality) and effectiveness objectives (i.e., product quality, stakeholder satisfaction, and business impact) (Auth et al., 2021). Even though efforts are made to advance technically, many projects still fail in terms of performance metrics (e.g., meeting deadlines, staying within budget, staying in scope, delivering quality, and meeting the client's expectations) - approximately 50% over the past 20 years (Strang and Vajjhala, 2022). The fact that projects are becoming increasingly more technically complex, with the added pressure to deliver in even shorter timeframes and reduced costs (van Besouw and Bond-Barnard, 2021), further impacts the successful execution of projects.

Project work ranges from definable (have-been-done-before, low uncertainty and risk) to high-uncertainty projects with high rates of change, complexity, and risk (Agile Practice Guide, 2017). Definable work projects would typically have similar past projects and, therefore, historical project data, which can be automated (Agile Practice Guide, 2017). This shift leads to the undertaking of more never-done-before (i.e. high-uncertainty projects) (Agile Practice Guide, 2017), which likely has little to no historical project data or information from similar projects.

2.2 Decision-making in project management

Project managers tend to rate their decision-making ability above average (Virine and Trumper, 2019). However, project managers were found to be ineffective decision-makers (McCray et al., 2002). This is concerning since managing a successful project includes making multiple critical decisions (Secundo et al., 2022). Thus, it is not surprising that projects continue to fail. Among other reasons, such as poor communication, mismanagement of stakeholders, and improper problem-solving, poor decision-making is the main reason why projects fail (Rumeser and Emsley, 2018).

Decision-making is integral to project success (Barcaui and Monat, 2023). PDM is the process of making decisions that affect the outcome of a project (i.e., success and performance) in terms of cost, time, scope, and quality from the pre-project phase through to completion. One of the first project decisions is project selection, which falls in the pre-project phase (Mariani and Mancini, 2023). Other critical decisions include "growth, problem shifting, goals balancing, escalation, rewarding, resource allocation, problem fixing and cooperation" (Secundo et al., 2022). There are two main decision-making types (Rumeser and Emsley, 2018). Firstly, logical decision-making is objective when presented with quantitively and explicit options and alternatives, which can be structured with mathematical methods (Rumeser and Emsley, 2018).

Secondly, intuitive decision-making, which is subjective and unstructured (i.e., not easily quantifiable), relies on the decision-maker's experience (Rumeser and Emsley, 2018).

Strategic decisions are usually complex and require suitable decision-making analysis tools. Experience is also an essential element in decision-making, specifically in complex environments (Rumeser and Emsley, 2018). For project managers and decision-makers to make sound decisions, high-quality information is required (i.e. poor information quality leads to poor decision-making) (Caniëls and Bakens, 2012). A project manager's decision-making capability is affected by three elements: the lack of complete and accurate information, cognitive limitations in interpreting the information, and the finite available time to make the decision (Secundo et al., 2022). Therefore, strategic decisions can be negatively impacted by the absence of live quality data and real-time reporting (van Besouw and Bond-Barnard, 2021). If project decision makers (i.e., usually project managers) do not have complete knowledge when faced with a problem, rational decision-making is limited or not possible, all possible scenarios cannot be analysed within the time constraint, and ultimately results in decisions being made based on limited information and heuristics limiting optimal outcomes (Shick et al., 2023).

Effective PDM is supported by project intelligence (PI). The term PI was first mentioned in a PM context in a 2004 project-related article, where specific characteristics were highlighted to obtain data and information in a timeline or real-time (Mikulis, 2004). Some of the key performance indications for PI, identified by the author, include centralized and collaborative project knowledge, accessibility through a web-based portal interface (i.e., cloud-based system), and what-if modelling (e.g., scenario planning to analyse outcomes before committing to a decision) (Mikulis, 2004). On the other hand, Mishra et al. (2022) define intelligent PM as automated routine tasks/processes using AI to reduce human intervention so that the project manager can use AI to augment their decision-making capabilities.

More recently, Hans and Mnkandla (2017) noted that PI is to PM what business intelligence is to business. Business intelligence is an umbrella term aimed at enhancing and optimizing decision-making and performance through data analysis and information, which includes applying tools and practices (Antunes et al., 2022). Therefore, PI is the application of tools and practices to improve and optimize PDM (enabling data-driven decision-making) and performance through real-time project data analysis and information. Project data and information will require decision-makers (project managers) to have PI. However, many PM practices rely on manual data capturing, often fragmented, unstructured, or undocumented. This data/information is frequently gathered across borders, and by the time it is compiled, it may no longer be relevant. Therefore, appropriate information management will be required, supported by/ facilitated in an Information System, or this case, a PMIS.

2.3 Project management information system

To make rational and informed decisions, one requires timely, high-quality, and accurate information (Caniëls and Bakens, 2012, Secundo et al., 2022). As mentioned, appropriate information management is required to ensure PI. A PMIS is a computer-based information technology software system that optimizes project performance in terms of efficient management and distribution of project resources, time, and information (van Besouw and Bond-Barnard, 2021). To optimize project performance, the PMIS generates, stores, manages, and presents project data and key performance indicators, which improves decision-making (van Besouw and Bond-Barnard, 2021). It is thus a decision-making support tool for project managers (Caniëls and Bakens, 2012).

However, many of the current PM practices still heavily rely on human input and manual data-capturing (van Besouw and Bond-Barnard, 2021, Mishra et al., 2022). Thus, van Besouw and Bond-Barnard (2021) highlighted the potential of applying AI in PMIS, which can analyse vast amounts of project data to identify patterns and anomalies and communicate the information to project stakeholders, providing insight to make actionable decisions. Such an advanced PMIS would be able to support more complex projects, which enables proactive PM through live real-time data and information that are intelligently analysed and easily accessible to project stakeholders (van Besouw and Bond-Barnard, 2021). van Besouw and Bond-Barnard (2021) developed a conceptual framework for such an advanced PMIS, called a Smart PMIS (SPMIS), and identified the following ideal characteristics: "increasing efficiency and time savings, accessibility to project information, automated data capturing and validation, flexibility and adaptability, simplicity of system and intelligence."

2.4 Artificial intelligence technology and categorization

AI has been defined in many publications, with equally as many variances. Mariani and Mancini (2023) defined AI as "all the knowledge involving the effort to make a machine intelligent – where the concept of intelligence relates to the ability to perform activities such as reasoning, knowledge capture, and representation". AI can be applied in multiple ways, but it is often classified into two main categories based on its employment purpose. These two categories are General (also known as Strong) and Narrow AI (Mariani and Mancini, 2024).

General or strong AI systems are identified by their ability to learn, grasp, and execute complex intellectual tasks in an adaptable manner that is not limited to individual pre-programmed tasks, unlike narrow AI (Mariani and Mancini, 2024). Such abilities are compared to human-like qualities, for instance, problem-solving, learning, interpretation, and natural language understanding (Mariani and Mancini, 2024). Meanwhile, narrow AI is designed to perform predefined tasks within a defined domain to solve a specific problem (Mariani and Mancini, 2024). Narrow AI systems usually learn or train on historical data to improve the model's performance (Mariani and Mancini, 2024). However, this requires humans to design/map in and outputs and define the domain's rules to ensure that generated outputs are accurate and consistent (Mariani and Mancini, 2024). Narrow AI has already been applied in multiple industries to aid decision-making, forecasting, and optimization. However, the application of general AI (specifically a system capable of emulating human intelligence) is still in development. Thus, the application of AI in PM in this context is categorized as narrow AI.

2.5 Artificial intelligence in project management

Given the inherently unique characteristics of projects, PM may not initially appear well-suited for AI applications (Auth et al., 2021). There is a shift of taking on more technically complex projects, with added pressure to complete them faster and at lower costs to meet growing competition and satisfy stakeholder expectations (van Besouw and Bond-Barnard, 2021). Furthermore, AI algorithms require extensive data for training, but project data is often fragmented and captured manually, if at all (van Besouw and Bond-Barnard, 2021, Mishra et al., 2022). This section will cover the application of AI in PM (including project phases and knowledge areas).

2.5.1 Project process groups

The academic and industry-recognized standard for PM practices, the PMBOK Guide formed the basis of this study and defines five process groups in the PM life cycle, namely: initiation, planning, executing, monitoring and controlling, and closing (PMBOK® Guide, 2021).

Literature regarding the utilization of AI within PM process groups predominantly focuses on quantitative dimensions, as numerical data is inherently more adaptable to processes with AI algorithms (Mariani and Mancini, 2024). This was also evident in the study of Hashfi and Raharjo (2023) on mapping challenges and the impacts of AI on PM process groups. From their structured literature review of 34 articles from 2019 to 2023, the majority of the articles focused on planning (i.e., 55.9%) and monitoring and controlling (i.e., 47.1%) (Hashfi and Raharjo, 2023).

Mariani and Mancini (2024) highlighted the application of AI in three specific phases: the pre-project phase (which can also be interpreted as the pre-sales phase of tenders and portfolio selection), the planning phase, and the monitoring progress in the execution phase. One of the first project decisions where AI could provide support is in this pre-project (or pre-sales) phase, where the organization needs to decide whether or not to submit a proposal (i.e. a quote or bid) for a tender (Mariani and Mancini, 2024, Taboada et al., 2023). In the pre-project phase, AI can support decision-making by analysing and predicting key performance indicators (e.g. risks, rewards, strategic goals, and resource availability) (Mariani and Mancini, 2024). Furthermore, at the onset of a project, Machine Learning (ML) can provide valuable insights and predictions on project success based on early critical success factors and historical data (i.e. past projects) (Mariani and Mancini, 2023, Hashfi and Raharjo, 2023). The application of an AI tool in a multi-project-based company can prove beneficial through supporting decision-making, such as project selection (Hashfi and Raharjo, 2023), and improving portfolio development efficiency (Mariani and Mancini, 2023). Thus, AI could be an effective tool in the pre-project and execution phases (Mariani and Mancini, 2023).

Most literature focused on the application of AI in project planning, and a significant focus is placed on its use in project risk assessment (Mariani and Mancini, 2024). Even though projects still fail at a similar rate (Strang and Vajjhala, 2022), Hashfi and Raharjo (2023) attribute the potential of improved project success rates and outcomes to the use of ML/AI tools in PM processes. It can potentially enhance risk assessment, increase the reliability of project selection, improve cost estimation accuracy, and support decision-making through real-time data analysis (Hashfi and Raharjo, 2023). A global study conducted in 2023 also reported that 74.79% of experts recognize AI's potential to improve project execution, decision-making, and alignment with strategic goals (Nieto-Rodriguez, 2023). Additionally, 41.06% of experts observed substantial improvements in project execution since adopting AI tools (Nieto-Rodriguez, 2023). Since such a tool could identify hidden patterns and trends from comprehensive historical project data otherwise overlooked, project managers would be better equipped to make more informed decisions (Mariani and Mancini, 2024). A systematic literature review examined the application of AI specifically in PM performance domains (Taboada et al., 2023). The study found that the majority of performance domain-related papers addressed the planning domain (i.e. proactively developing a plan to deliver the project deliverables and outcomes) (PMBOK® Guide, 2021, Taboada et al., 2023).

The use of AI to monitor progress during the project execution phase is well-researched (Mariani and Mancini, 2024). Performance monitoring was identified as one of the top three areas most impacted by AI in a global 2024 survey (PMI, 2024). Many highlight the benefits and impact of AI/ML and others (e.g., lean techniques, decision support systems, and enterprise resource planning tools on project execution). Hashfi and Raharjo (2023) summarised these outcomes in their systematic literature review as improved decision-making, productivity, project delivery time and quality, reduced project costs and waste, and optimized resource allocation. The first global study exploring AI within PM surveyed 772 experts from 95 countries and found that many reported significant improvements in project execution after adopting AI tools (Nieto-Rodriguez, 2023). Additionally, 37.69% of experts believe that AI can substantially improve strategy execution, particularly improving project delivery, decision-making, and strategic alignment (Nieto-Rodriguez, 2023).

The application of a tool capable of complex data analysis, forecasting, and risk identification (e.g., predicting possible future outcomes and completion dates based on historical project data) would empower project managers to handle challenges proactively instead of reactively (Mariani and Mancini, 2024, Hashfi and Raharjo, 2023). Although Mariani and Mancini (2024) presented the application and the impact of AI on cost, quality, scope, quality, schedule, communication, and stakeholder management within the project execution phase, the application of AI in PM knowledge areas will follow.

2.5.2 Project knowledge areas

The ten knowledge areas in the PM life cycle are integration, content and scope, time, cost, quality, procurement, risk, human resources, communication, and stakeholder management (PMBOK® Guide, 2021). Fridgeirsson et al. (2021) surveyed PM experts to examine the potential impact of AI on PM over the next ten years. Their findings indicated that, among the ten knowledge areas, project cost, schedule, and risk management are expected to benefit the most from AI.

Project cost estimation is a popular topic in the literature (Auth et al., 2021) and is perceived to be most impacted by AI, with 64% of respondents rating it as having a high to very high effect (Fridgeirsson et al., 2021). This is because AI proves to be especially useful in applications involving historical data (Fridgeirsson et al., 2021). The cost estimation functionality of AI models is based on their training on several cost drivers to provide specific cost forecasts tailored to a particular project situation (Auth et al., 2021). Linking back to the PM process groups, AI can add value during the planning phase through project timeline/ duration estimation and forecasting based on historical project data (Auth et al., 2021). Mariani and Mancini (2023) argue that processes with a mathematical nature, as well as those that are standardized and repetitive, are most suitable for automation. Specific cost and schedule management activities can already be executed by computer-based algorithms, paving the way for the implementation of AI (Mariani and Mancini, 2023). Interestingly, project budgeting was identified as one of the areas with low impact from AI in a global 2024 survey, which suggests that this project domain still relies on traditional approaches (PMI, 2024). This further highlights the potential for future AI integration. In addition, their study also identified project time management and scheduling as one of the top three areas most impacted by AI, showing that AI is used to improve analytical capabilities and efficiency (PMI, 2024).

Literature on the application of AI in risk management focuses on determining risk factors, assessing their potential implications, and suggesting appropriate risk mitigation strategies to ensure that project objectives are met (Auth et al., 2021). The use of AI in risk assessments typically has two objectives: minimizing subjectivity in expert evaluations and accounting for the complex interrelationships among multiple risks (Mariani and Mancini, 2024). Furthermore, AI can also be used for risk mitigation and to plan contingencies. AI algorithms can assist in identifying, estimating, and optimizing mitigation and contingency responses while accounting for constraints (e.g. allocated budget for implementation) (Mariani and Mancini, 2024). Mariani and Mancini (2024) summarised specific AI models investigated for these applications.

Based on the study conducted by Fridgeirsson et al. (2021), integration management is also expected to significantly benefit from introducing AI as its activities align well with the key features of AI (Mariani and Mancini, 2023). Integration management involves "the coordination of activities across all PM areas and process groups" (PMBOK® Guide, 2021). As Mariani and Mancini (2023) interpreted, integration management refers to gathering and combining inputs from various procedures and organizing this data to provide helpful information and insights to support decision-making. In the context of PM, AI's fundamental functions are to analyse large amounts of data to determine trends and patterns, classify information, and generate forecasts to aid project managers in their decision-making processes (Mariani and Mancini, 2023). An example of AI application in integration management is predicting project success using early project critical success factors based on historical project data (Mariani and Mancini, 2023). Despite its potential, a 2020 study by the International Project Management Association (IPMA) in collaboration with PwC on the impact of AI in PM confirmed that there have been only a few successful cases of ML implementation in PM (IPMA, 2020, Mariani and Mancini, 2023). Although the adoption of AI in PM is still in its infancy, interest in its application is growing (PMI, 2024). Moreover, by 2030, ML use in PM is expected to become more widespread (IPMA, 2020, Mariani and Mancini, 2023).

Quality management, which ensures a desired level of quality by measuring activity quality and implementing necessary adjustments, is another knowledge area that can significantly benefit from AI (Mariani and Mancini, 2023, Fridgeirsson et al., 2021). Literature on AI applications in quality management primarily centres around classifying and evaluating project outcomes (Auth et al., 2021). Similar to risk management, AI can be used to identify quality concerns at an early stage through continuous measurement, allowing for timely corrective actions to maintain the desired quality level (Auth et al., 2021, Mariani and Mancini, 2023). Mariani and Mancini (2023) provide examples of how virtual assistants have been used in quality and communication management.

The knowledge areas requiring human skills such as empathy, leadership, critical listening, negotiation, understanding of needs, and emotional intelligence) are expected to be the least impacted by AI (Mariani and Mancini, 2023, Fridgeirsson et al., 2021). These areas include resource, stakeholder, and scope management (Mariani and Mancini, 2023, Fridgeirsson et al., 2021). However, some of the processes within these areas have the potential to be automated (e.g., auto resource allocation (Mariani and Mancini, 2023). This is also echoed in a global 2024 survey, which suggests that these domains (specifically stakeholder management and project communication) still rely on traditional approaches (PMI, 2024).

Mariani and Mancini (2024) highlight the potential for AI to replace human project managers in quantitative domains of PM, while qualitative domains that rely on humans, interpersonal tasks, and abstract capabilities are more prone to be augmented by AI than entirely replaced. Many share the view that an AI tool in PM should serve as support for human project managers (Nieto-Rodriguez, 2023, IPMA, 2020, Auth et al., 2021). Additionally, the study conducted by Nieto-Rodriguez (2023) found that experts generally expressed a positive outlook on using AI in PM, with 80.4% indicating they are somewhat to very likely to invest in exploring its potential. However, the application of AI in PM is still not widespread, and numerous challenges/barriers continue to hinder its full implementation in practice.

2.6 Factors of artificial intelligence application in project management

Given the inherently unique characteristics of projects, PM may not initially appear well-suited for AI applications (Auth et al., 2021). As mentioned, AI algorithms require extensive data for training, but project data is often fragmented and captured manually (if at all) (van Besouw and Bond-Barnard, 2021). Small projects with limited resources are a barrier to implementing AI since it requires a large amount of historical project data (Sahadevan, 2023).

Auth et al. (2021) investigated both the PM requirements for an AI tool and the AI requirements for its application within PM. Considering the mutual AI and PM requirements/factors, it would support the design and implementation of a tailored AI solution within PM (Auth et al., 2021). Auth et al. (2021)'s AI and PM requirements, factors, and implications should be considered when designing and implementing a tailored AI solution within a PM domain. PM requirements include project characteristics, PM method, comprehensibility, and the scope and degree of standardization of PM practices (Auth et al., 2021). On the other hand, AI requirements include factors related to data, activity characteristics and technology, and domain understanding (Auth et al., 2021). Project and organizational factors such as type, size, structure, digital strategy, strategic alignment, and available funds should also be considered (Auth et al., 2021, Sahadevan, 2023, Fridgeirsson et al., 2021, Alshaikhi and Khayyat, 2021, Brandas et al., 2023).

Multiple studies highlight challenges, barriers, and factors to consider when applying AI to PM. IPMA and PwC conducted a global survey in 2020 on the impact of AI on PM, where they presented the AI adoption drivers and barriers in PM. Additionally, the PMI Sweden conducted a global AI and PM chapter-led survey in 2024, also addressing risks (IPMA, 2020, PMI, 2024). Both studies highlighted that the most prevalent barrier to AI in PM is the limited understanding of AI technologies (IPMA, 2020, PMI, 2024). Many identify human-related barriers, such as a lack of AI understanding, expertise to develop, implement, and use an AI tool in PM, as well as a shortage of well-trained technical personnel, as significant challenges to AI implementation in PM (Alshaikhi and Khayyat, 2021, Auth et al., 2021, Sahadevan, 2023, Fridgeirsson et al., 2021, Hashfi and Raharjo, 2023, Brethenoux and Karamouzis, 2019, Mariani and Mancini, 2023, Barcaui and Monat, 2023).

Other human-related factors/barriers include reluctance to change/adopt, job displacements (where upskilling would be required), moral decision-making making, and bounded rationality (Brandas et al., 2023, Hashfi and Raharjo, 2023, Miller, 2021, Shick et al., 2023, PMI, 2024, Barcaui and Monat, 2023). If decision-makers do not have comprehensive knowledge when faced with a problem, rational decision-making is limited or not possible, all possible scenarios cannot be analysed within the time constraint, and ultimately results in decisions made based on limited information and heuristics limiting optimal outcomes (i.e. bounded rationality) (Shick et al., 2023). AI has the potential to "bridge the decisional gap between bounded and full rationality" (Shick et al., 2023). However, almost 75% of experts in a 2023 global survey expressed concern regarding the likely development of ethical challenges when using AI-based decision-making processes (Nieto-Rodriguez, 2023). Many highlight the importance of building an ethical AI tool and ethical decision-making. Bias and fairness of AI algorithms are critical to limiting biased decision-making (PMI, 2024, Barcaui and Monat, 2023). The AI system should be protected regarding data security and privacy safeguards and comply with regulatory requirements, to name a few (PMI, 2024, Sahadevan, 2023, Hashfi and Raharjo, 2023, Miller, 2021).

Although not explicitly defined for PM purposes, Miller (2021) identified six AI product success groups and their corresponding factors for implementing AI for moral decision-making. The six groups are: 1) source data qualities, 2) training data qualities, 3) model and algorithm qualities, 4) user interface qualities, 5) system configuration, and 6) data privacy and confidentiality (Miller, 2021). These success groups and their factors are also relevant when implementing AI in a PM context. As mentioned, an AI tool/system needs comprehensive project data to train predictive models to meet model accuracy (Mariani and Mancini, 2023). Therefore, many data and algorithm-related factors such as data quantity, quality, accuracy, and availability should be considered and could pose a challenge when designing and implementing an AI system in PM (PMI, 2024, Alshaikhi and Khayyat, 2021, Sahadevan, 2023, Hashfi and Raharjo, 2023, Mariani and Mancini, 2023, Auth et al., 2021). Furthermore, an information technology software system requires project data. However, this project data needs to be in a usable digitalized form. Therefore, not only will some level of digital maturity (e.g. digitalization) and data management be required, but the company's digital transformation strategy should also include AI (Brethenoux and Karamouzis, 2019, Sahadevan, 2023). Integrating an AI system into existing systems and platforms, which would allow interoperability, poses another challenge and could be time-consuming in large organizations. To successfully implement such a tool in PM, project managers' skills will need to be reconfigured to cater to the data management demand (Mariani and Mancini, 2023).

Brandas et al. (2023) conducted a SWOT analysis to investigate the strengths, weaknesses, opportunities, and threats regarding AI in PM, focussed on the health, energy, and education sectors. Strengths, such as increased efficiency, optimization, enhanced analytics and forecasting, and task automation, highlight the advantages of AI in PM. Weaknesses or limitations of AI in PM include dependence on data quality, high upfront investment, and reluctance to change/adopt AI in PM. Opportunities include improved decision-making, reduced human error, increased productivity, and personalized services. Lastly, threats, such as data security risks, social and ethical concerns, and technology overreliance, pose challenges to successful AI implementation in PM.

Hashfi and Raharjo (2023) explored the challenges and impacts of AI implementation in PM with a systematic literature review of 34 scientific articles. They specifically focussed on mapping these challenges and effects into the PM process groups (i.e. initiating, planning, execution, monitoring and controlling, and closing) to understand the integration of AI in PM better. Some of the challenges and impacts identified by Hashfi and Raharjo (2023) include data quality and accuracy, model selection, user interface development, system integration, technology understanding adoption, and resistance to change. Hashfi and Raharjo (2023) also provide AI models, tools, and techniques typically used in each process group and possible solutions to challenges.

Taking inspiration from Miller (2021)'s success groups and based on the AI and PM factors, requirements, and barriers identified in the literate review, seven main groups, which will be referred to as success groups, were identified as 1) Data, 2) Model and Algorithm, 3) User Interface and System Development, 4) Safety and Security, 5) Project, 6) Organization and 7) Human-related aspects. Table 1 provides a summary of the AI and PM requirements, barriers, and factors mapped to the success groups. As identified in this literature study, these are factors to consider when implementing AI in PM.

Table 1 AI and PM factors, requirements, and barriers to consider when implementing AI in PM

Factor	AI Req.	Barrier	PM Req.	Reference
Data				
Accessibility/ Availability	x	x		(PMI, 2024, Auth et al., 2021, Alshaikhi and Khayyat, 2021, Miller, 2021)
Transparency	x			(Miller, 2021)
Quality and Relevance	x	x		(Auth et al., 2021, Miller, 2021, PMI, 2024, Brandas et al., 2023, Hashfi and Raharjo, 2023, Brethenoux and Karamouzis, 2019, Sahadevan, 2023)
Quantity	x	x		(Sahadevan, 2023, Auth et al., 2021, Mariani and Mancini, 2023, Alshaikhi and Khayyat, 2021)
Storing	x	x		(Auth et al., 2021)
Digitalization	x	x		(Brethenoux and Karamouzis, 2019)
Model and Algorithm				
Selection and development		x		(Brethenoux and Karamouzis, 2019, Hashfi and Raharjo, 2023)
Transparency	x			(Miller, 2021)
Consistency	x	x		(PMI, 2024, Miller, 2021)
Accuracy	x	x	x	(Mariani and Mancini, 2023, Miller, 2021, PMI, 2024)
Interpretability	x	x		(Miller, 2021, Hashfi and Raharjo, 2023)
Model Validation	x	x	x	(PMI, 2024, Sahadevan, 2023)
Algorithm renewal and retraining	x			(Miller, 2021, Auth et al., 2021)
User Interface (UI) and System Development				
UI Front-end transparency	x		x	(Miller, 2021, Auth et al., 2021)
Simplicity and clear presentation		x	x	(Auth et al., 2021)
Standardized processes for UI and system development	x	x		(Auth et al., 2021, Mariani and Mancini, 2023)
Interoperability		x	x	(Auth et al., 2021, Alshaikhi and Khayyat, 2021, Hashfi and Raharjo, 2023, Sahadevan, 2023)
Safety and Security				
Data and Model Security	x	x		(Auth et al., 2021, PMI, 2024, Brandas et al., 2023)
Privacy Safeguards	x	x		(PMI, 2024, Miller, 2021)
Confidentiality	x			(Miller, 2021)

Policies and regulations	x	x		(PMI, 2024, Miller, 2021)
Ethical concerns	x	x	x	(Auth et al., 2021, Sahadevan, 2023)
Project				
Project Size		x	x	(Sahadevan, 2023)
PM Method		x	x	(Auth et al., 2021)
Project Complexity and Uniqueness		x	x	(Auth et al., 2021, Alshaikhi and Khayyat, 2021, Hashfi and Raharjo, 2023)
Project Scope			x	(Auth et al., 2021)
Project Goal			x	(Auth et al., 2021)
Organization				
Strategic Alignment		x		(Auth et al., 2021)
Digital strategy		x		(Sahadevan, 2023)
Organization Type		x		(Auth et al., 2021)
Available funds		x		(Sahadevan, 2023, Fridgeirsson et al., 2021, Alshaikhi and Khayyat, 2021, Brandas et al., 2023)
Human-related aspects				
Technology understanding and skills		x		(Auth et al., 2021, Mariani and Mancini, 2023, Fridgeirsson et al., 2021, IPMA, 2020, PMI, 2024, Hashfi and Raharjo, 2023, Brethenoux and Karamouzis, 2019)
Considering bounded rationality		x		(Shick et al., 2023)
Change management		x		(Brandas et al., 2023, Hashfi and Raharjo, 2023)

2.7 Conceptual frameworks

Although there exist conceptual models on AI in PM, such as those proposed by Engel et al. (2021) and Dzhusupova et al. (2024), there is a lack of comprehensive guidelines and frameworks to assist project managers in identifying where to begin, which critical factors to consider, what changes or developments are necessary, and the specific expertise required. Engel et al. (2021) empirically investigated AI's unique characteristics (i.e., experimental character, context sensitivity, black box character, and learning requirements) and how to address organizational socio-technical challenges. To increase the success rate of AI implementations, they provide cause-effect relationships between AI characteristics, PM challenges, and organizational change. Dzhusupova et al. (2024) developed a practical guide for practitioners to choose the correct/optimal approach to integrating AI into engineering companies. The framework presents multiple factors that impact the path to AI project development (e.g., in-house development or outsourcing), which could assist companies in creating business value accordingly.

To address the need for a structured practical instrument for organizations to design and apply AI solutions for PM, Auth et al. (2021) developed a conceptual framework for using AI in PM. The framework presents important concepts for applying AI in PM by considering the AI requirements for the PM application domain and the PM requirements for the AI solution domain. The framework comprises six components: the business domain, application domain PM, benefits, solution domain AI, use case, and AI system for PM (Auth et al., 2021). This model was reviewed to better understand the relationships between factors – especially the mutual requirements within the AI solution and PM application domain. However, some shortfalls of the conceptual framework proposed by Auth et al. (2021) include the following:

- It is unclear which factors are more important to consider than others.
- The AI system factors are not clearly defined. The AI solution domain is also unclear.
- Specific AI and PM requirements and barriers are not addressed or presented in the framework.
- The application of AI to support decision-making is not presented.

3 Methodology

This study adopted a mixed-method approach with a semi-structured focus group interview and an online survey, as shown in Figure 1. The two approaches were used to identify factors to consider when implementing AI in PDM and if there's a level of importance to consider. The findings were used to develop a conceptual framework for implementing AI in PDM, addressing the research objective.

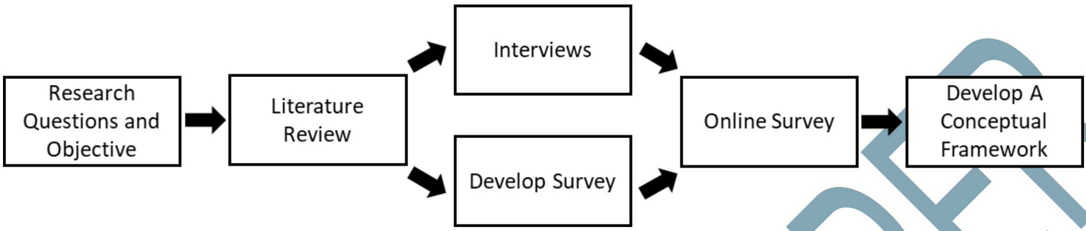

Fig. 1 The research strategy

3.1 Qualitative – interview

The semi-structured focus group interview was conducted with seven individuals from the same South African project-based engineering company. The participants were purposefully chosen based on their expertise in strategic decision-making, PM decisions, more technical knowledge of software, systems, and automation/AI, and industry experience in a project-based company. This was done to identify what is limiting effective PDM, what could be changed to improve it, and what factors should be considered to implement AI in PDM (and why). This would also verify factors identified in the literature, and if other factors come to light in the interview. Each research participant's designation in this project-based company has been summarised in Table 2.

Table 2 Semi-structured focus group interview participant designations

No	Job Title	Job Description
1	Senior Full Stack Developer	Front- and back-end software development of systems.
2	US Brand President	Oversee US projects, on-site coordination, project feedback, and financial management. Support the SA CEO with risk management and managing client expectations.
3	Automation Manager	Handle and manage automation engineering tasks within an automated system.
4	General Manager	Managing finances directly and indirectly related to projects and resource planning.
5	Senior Systems Engineer	Functional and operational system design, software scope specifications, and system integration with the client.
6	CEO	Oversee projects focusing on crisis/ risk management and managing client expectations.
7	Project Engineer	Manage external and internal project teams to meet milestones and quality.

The semi-structured focus group interview consisted of 15 questions, with probing questions to prompt elaboration on specific topics. It lasted 150 minutes and was conducted in three sessions. All the sessions were voice-recorded and transcribed. After that, the transcription was coded in ATLAS.ti 24.1.1 using thematic analysis.

3.2 Quantitative - survey

Following the more explorative and open-ended interviews focussed on qualitative data, an online survey was conducted to gather quantitative data from South African University's Master of Engineering Management (MEM) students and alumni. These participants come from various engineering and science backgrounds, industries, companies, and experience. Furthermore, they were purposefully chosen based on their interest and even expertise in Engineering Management topics (which includes AI and PM).

The online survey comprised 20 structured questions distributed among the 2024 MEM students and alumni. With a total of 34 responses, the survey response rate was approximately 16%. Of the surveyed participants, more than half have designations related to PM (i.e., project- managers, leads, controllers, engineers, program and portfolio managers). Still, a handful of participants are in software/AI/automation-related and other fields. The participants are involved in a wide range of industries, with the majority in Engineering, Construction, and Mining. Most participants are involved in multiple projects at once (averaging 5.14 projects) over several months (29% over 24-36 months, 26% over 12-24 months, and 27% over 6-12 months). Descriptive statistic methods were used to analyse the survey data in IBM SPSS Statistics 29.0.0.0 and Microsoft® Excel® (Version 2410) to determine which factors are more important than others to consider when implementing AI in PDM.

4 Findings

4.1 Interview

It is essential to understand why projects continue to fail. When asked, participants' most prominent reason for project failure was related to PM (specifically poor scope and expectation management and poor planning). Project failure can be due to company, PM, and decision-making factors. Furthermore, one of the interview's objectives was identifying what limits effective PDM. The two main categories were external and internal factors to a company or project. Participants strongly agreed that poor communication was one of their main frustrations when making decisions. However, when asked to describe how they make decisions, few participants could provide a straightforward and effective decision-making process or strategy.

Specific patterns and phrases emerged when asked to provide the critical factors to consider when using AI for PDM (which also included limiting factors). The Data and Model category and its subfactors were discussed most frequently, with specific emphasis on data accuracy (or a measure of accuracy), data quantity, traceability, and digitalization (i.e., digital processes). Furthermore, the Human factor was also prominent. Throughout the interview, participants emphasized the importance of machine and human collaboration, where AI should be used only as a tool and not to replace the human PM. In other words, without approval, the AI-enabled tool should not have the ability or capability to make project decisions on the PM's behalf. This is also linked to the factor of trust in AI.

The last two questions asked participants to provide possible effects of an AI-enabled tool on project performance and PDM. The responses to both questions fell into the same categories: decision-making and Productivity effects. Most of the responses focused on the positive effects such a tool could have on improving decision-making. Poor decision-making and poor communication were identified as possible reasons for project failure. Furthermore, poor communication was identified as an internal factor limiting effective decision-making. Therefore, project performance could improve if decision-making is improved (with improved communication). However, although communication management is one of the identified knowledge areas in which AI could improve, the human factor remains.

4.2 Important factors for AI implementation in PDM

The online survey section focussed on AI success groups used a 5-point Likert-type scale for the level of importance of a specific factor, measured from not important (1) to very important (5). An ANOVA single-factor test was conducted to determine whether a statistically significant difference existed between the success group/ factor means. However, a Friedman test confirmed a statistically significant difference between the groups and factors. The Wilcoxon post-hoc test was conducted to determine whether there was a statistically significant difference between each success group - resulting in insignificant differences between specific factors.

Even though the post-hoc test indicated that there is, in some cases, no statistically significant difference between specific group and factor means, the results presented in Table 3 are ranked based on their mean ranks (purely based on participants' responses). Therefore, although the presented factors in Table 3 are not exhaustive, they could provide a starting point for important factors/ AI success groups to consider when applying AI in PDM.

Table 3 AI success groups and factor importance (both ranked from most to least important)

1) Data	**2) Safety and Security**
1. Data Transparency 2. Data Quality and Relevance* 3. Data Accessibility/ Availability* 4. Digitalization* 5. Data Quantity* 6. Data Storing* 7. Automatic data capturing	Confidentiality Data and Model Security* Policies and regulations* Privacy Safeguards* Ethical concerns (e.g., bias and discrimination) * *In no particular order.*
3) Model and Algorithm	**4) Human**
1. Transparency 2. Accuracy* 3. Interpretability* 4. Consistency* 5. Model Validation* 6. Algorithm renewal and retraining 7. Automated analysis 8. Selection and development for solution design* 9. Predictive model	1. Considering bounded rationality* 2. Technology understanding and skills* 3. Change management to manage reluctance to change* 4. Critical thinking to understand the tool's limitations
5) User Interface and System Development	**6) Organization**
1. Interoperability* 2. Simplicity and clear presentation * 3. Flexibility and adaptability of reporting system to the organization and project requirements 4. Standardized processes for user interface and system development* 5. Collaborative with natural language processing 6. Establish the operator's knowledge base 7. UI Front-end transparency	1. Digital strategy* 2. Strategic alignment* 3. Available funds* 4. Organization Type (e.g., project-based) * 5. Product development strategy
7) Project	
1. Project Complexity and Uniqueness* 2. Project Scope 3. Project Goal 4. Product/project maturity 5. PM Method (e.g., waterfall/ agile, etc.) *	

6. Project Size*
7. Project Industry Type

Success Groups		Success Factors		Barriers	*

4.3 Proposed conceptual framework

To address the research objective, the findings from the two research questions were used to develop a conceptual framework for implementing AI in PDM. This conceptual framework is illustrated in Figure 1 The seven success groups, as presented in Table 3 are listed in order of importance (i.e., most to least important). Each of these success groups can further be broken down into success factors (also in terms of level of importance).

Before breaking down each success group in more detail, it is important to understand the different elements and domains illustrated in the framework. The main objective of applying AI (i.e., an AI system or solution) in PM is to provide benefits, taking the form of project success and performance such as efficiency objectives (i.e., time, cost, and quality) and effectiveness objectives (i.e., product quality, stakeholder satisfaction, and business impact) as proposed in the framework of Auth et al. (2021). Therefore, the AI solution domain aimed at improving PM can be found within the PM application domain, which is also part of the organizational domain (i.e., providing benefits to the project and organizational domain). Based on the AI requirements and barriers within the solution domain, the AI system is designed, developed, and tailored for the PM application domain (considering requirements and barriers). The three domain borders are purposefully indicated as dotted lines to illustrate no distinct separation between the domains and continuous interaction between them.

PM decision-makers ability to make effective decisions can be affected by the lack of complete and accurate information and the finite available time to make the decision (Secundo et al., 2022). As previously mentioned, project success (i.e., benefits) relies on effective PDM, which is enabled by project intelligence (i.e., tools to improve decision-making through real-time data and information). However, since project intelligence relies on data and information, appropriate information management will be required, supported by/ facilitated in a PMIS. van Besouw and Bond-Barnard (2021) recognized the potential of applying AI in PMIS, which provides insights to project stakeholders to make actionable decisions, and developed an SPMIS conceptual model. A SPMIS is an example of an AI system in PM (which can be found in the centre of the framework presented in Fig. **2**). However, certain success factors should be considered when designing and implementing such an information technology software system.

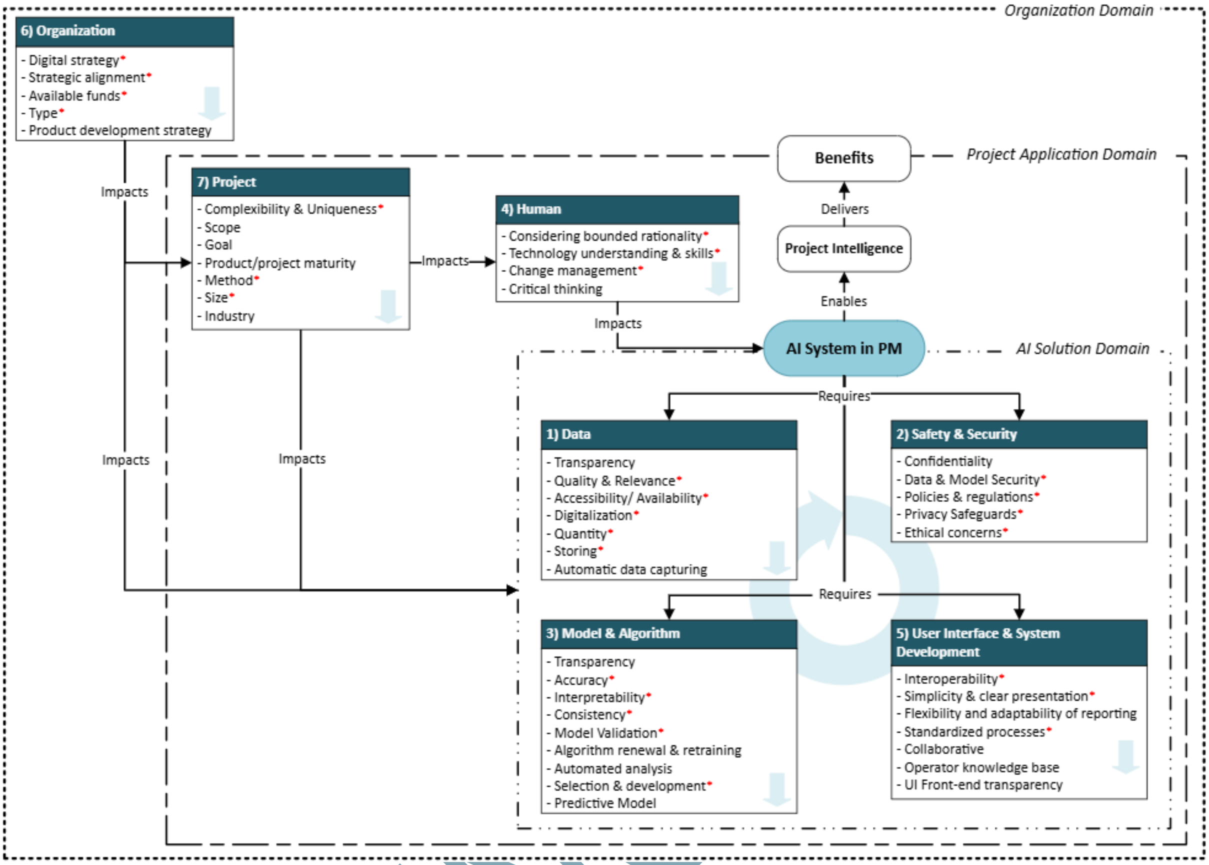

Fig. 2 Conceptual framework to implement AI in PDM

The Data, Model and Algorithm, User Interface and System Development, and Safety and Security success groups are found in the AI solution domain as it is required to design, develop, and implement the AI system in PM (i.e., they are AI solution requirements). Therefore, some factors could also be considered characteristics of an ideal AI system in PM. These success groups and their corresponding factors are not only impacted by groups and factors outside of the AI solution domain but also interact with and impact one another inside the AI solution domain, as indicated by the circular arrow.

The Data success group in Fig. **2** is considered the most important factor to consider. As previously mentioned, AI models rely on data for training and testing and are only as good as their data (i.e. garbage in, garbage out). This group consists of success factors related to data, ranked from most to least important: data transparency (for traceability of source data and context), data quality and relevance (it needs to reflect actual conditions), data accessibility/ availability, digitalization (i.e., creating digital processes with digitizing techniques), data quantity (for a data-driven environment), data storing (e.g., uniform procedures for storing data), and automatic data capturing (i.e., reducing or removing manual data capturing).

The Safety and Security success group is the second most important group to consider and applies to the AI solution and its success groups. As seen in Fig. **2** this group consists of equally important success factors related to safety and security: confidentiality, data and model security, policies and regulations, privacy safeguards, and ethical concerns (e.g., bias and discrimination), in no particular order. It is recommended that an AI policy be created in the organization to ensure that the AI system/tool is developed, implemented, and used ethically.

Following that is the Model and Algorithm success group. As previously mentioned, an AI model is a program trained on a dataset to recognize patterns or make decisions automatically. These models use algorithms to process relevant data inputs to generate designed outputs or achieve a specifically programmed task. This group consists of success factors, as seen in Fig. **2** and are ranked from most to least important: transparency (i.e., clearly explain decisions produced), accuracy (i.e., low false positives and error rates), interpretability (i.e., easy-to-understand explanations of predictions), consistency (i.e., same results. given same inputs), model validation (e.g., should include bias testing), algorithm renewal and retraining, automated analysis, selection and development for solution design, and predictive model (e.g., for scenario planning).

The last success group within the AI solution domain, User Interface and System Development, consists of success factors ranked from most to least important: interoperability (integration with other systems), simplicity and clear presentation (for non-specialist users), flexibility and adaptability of reporting system to the organization and project requirements, standardized processes for user interface and system development, collaborative with natural language processing, establish an operator's knowledge base and UI front-end transparency.

The Human success group is part of the project application domain, as shown in Fig. **2** since the AI solution is designed to support PDM (i.e., project managers). The AI solution must be designed, implemented, and accepted by individuals. Human-related aspects should be considered when designing the solution for the PM application domain, especially since a limited understanding of AI technologies is the most prevalent barrier to the use of AI in PM (IPMA, 2020, Nilsson et al., 2024). This group consists of human success factors ranked from most to least important: considering bounded rationality during decision-making, technology understanding and skills of AI and the solution/tool, change management to manage reluctance to change, and critical thinking to understand the tool's limitations. Despite the potential of AI in PM and decision support, results show that few currently have the expertise and understanding to manage, implement, and integrate AI in PM effectively. Therefore, investing in training and upskilling programs for project managers, teams, and decision-makers is crucial. Training should not only focus on the technical aspects of AI but also on developing critical thinking skills to understand its limitations and applications in PDM.

The Organization success group is part of the organization domain, as illustrated in Fig. **2** which interacts with the project application and AI solution domain (and indirectly with success groups inside the domains). This group consists of organizational success factors ranked from most to least important: digital strategy, strategic alignment, available funds, organization type (e.g., project-based), and product development strategy. A strategic plan for AI integration that aligns with the organizational goals and strategies (specifically the digital strategy) is recommended. The implementation plan should focus on the areas with the highest impact potential.

The Project success group is considered the least important group to consider. This group consists of project success factors ranked from most to least important: project complexity and uniqueness, project scope, project goal, product/project maturity, PM method (e.g., waterfall/ agile, etc.), project size, and industry type. Results show that the application of AI is not necessarily inappropriate for small projects with limited resources. Within the project domain, it was found that quantitative areas have the highest AI impact potential. This included the monitoring and controlling, planning and initiation process groups, and the time, risk, integration, and cost management knowledge areas.

Challenges and barriers within the success groups and their factors still exist when applying AI in PM. These barriers are indicated with a red star next to each factor, as illustrated in Fig. **2** . The 2020 IPMA and PwC global survey regarding the impact of AI in PM identified the top three most important steps to overcome the barriers to AI adoption as defining an AI strategy that is aligned with business goals, investing in AI talent and training, and establishing standards and methodologies for sound data-driven processes in projects (IPMA, 2020).

5 Discussion and conclusion

Projects are failing at a high rate despite technological advancements, possibly due to poor communication, scope and expectation management, and poor planning and decision-making. Decision-making is an integral part of project success. However, effective decision-making can be limited by internal or external factors. Furthermore, gathering relevant information for informed decision-making is limited in an increasingly complex project environment where project data is often fragmented and relies on manual capturing. Project decision-makers would be more confident when faced with an unforeseen event if they could formulate a real-time, accurate picture of the situation to test and respond appropriately. There is a growing interest in AI in PM and its potential to act as a decision-making support tool. However, even with the challenges and benefits of applying AI in PM already being explored and investigated in literature and industry, it is still unclear what factors should be considered to guide the implementation of AI in PDM. To address this problem, this study aimed to develop a conceptual framework to guide the potential implementation of AI as a tool for PDM. To meet this objective, the study was structured to answer two research questions, from which a conceptual framework was built.

A mixed-method research methodology approach was used for this study to answer the research questions and meet the research objective. The research methods included a semi-structured focus group interview company and an online survey. The interview aimed to identify what factors should be considered to implement AI in PDM, verify factors identified in the literature, and determine if other factors come to light in the interview. Seven AI success groups (i.e., Data, Model and Algorithm, User Interface and System Development, Safety and Security, Project, Organization, and human-related aspects) were identified, each with multiple success factors.

The survey aimed to quantify the importance of the factors that should be considered when implementing AI for PDM. In terms of the seven success groups and their factors, even though there is in some cases no statistically significant difference between specific means. As was presented in **Fehler! Verweisquelle konnte nicht gefunden werden.** the groups and factors are ranked based on their mean ranks (purely based on participants' responses). Therefore, although the presented factors in **Fehler! Verweisquelle konnte nicht gefunden werden.** are not exhaustive, they could provide a starting point for considering important factors/ AI success groups when implementing AI in PDM.

This research aims to serve as a starting point to equip project managers with a guide to identify important factors for implementing AI as a PDM tool. The successful implementation and application of such a tool in PM could improve decision-making and project performance. A conceptual framework was developed to address this aim. However, this study and the framework is not without its limitations, such as:

- A brief literature study on relevant topics and concepts about AI, PM, decision-making, and applying an AI-enabled tool to assist PDM. For future research, it is recommended that the proposed conceptual framework be expanded by conducting a comprehensive bibliographic analysis to ensure all factors, requirements, barriers, and possible tools are identified for implementing AI in PM. This could also include investigating other AI-related models and frameworks, such as those produced by Engel et al. (2021) and Dzhusupova et al. (2024).
- Even though this is an explorative study, the seven interview participants were not experts in PM or AI, and all work for the same engineering project-based company. For future research, it is recommended that the number of participants be increased and a more diverse group of expert participants be included.
- Similarly, although the online survey sample group came from various engineering and science backgrounds, industries, companies, and experiences, they were all from a specific small university

course (e.g., MEM). Additionally, the survey was in a closed-ended format, which could limit the identification of new factors and understanding of why specific responses were selected (e.g., little to no qualitative data). Thus, surveying with a larger sample group is recommended.

- Furthermore, the survey results were used to determine which factors are more important than others. In some cases, there was no statistically significant difference between the success group and factor means. Thus, a post-hoc analysis is recommended to determine whether there is a statistically significant difference between each listed factor. This means that the success group and factor ranking would be based on statistical significance instead of participant's responses.

Concerning future research, the following areas and topics could be investigated:

- The application and performance of the proposed conceptual framework (Fig. **2**) in different PM environments. This could also include highly complex projects (i.e., with little to no historical project data available).
- The influence of an AI-enabled decision-making tool on bounded rationality and cognitive biases.
- The ethical and legal implications of AI biases on PDM, cognitive biases, and project outcomes.

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