REVIEW OF THE IMPACT OF ARTIFICIAL INTELLIGENCE ON PROJECT MANAGEMENT PRACTICES: INSIGHTS FROM INDUSTRY EXPERTS IN GHANA

By

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Dalhousie University is located in Mi'kma'ki, the

ancestral and unceded territory of the Mi'kmaq.

We are all Treaty people.

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ABSTRACT

Advancements in artificial intelligence (AI) are reshaping organizational operations and strategic decision-making, with significant implications for project management (PM). As a core organizational function, PM plays a pivotal role in achieving corporate objectives through the successful execution of projects. The integration of AI into PM processes offers opportunities to enhance efficiency, optimize resource allocation, and improve decision-making. Despite growing scholarly interest, existing literature lacks a comprehensive framework that holistically examines AI's influence across PM knowledge areas, process groups, and performance domains. Furthermore, methodological limitations persist, as prior studies predominantly employ singular approaches such as systematic literature reviews (SLRs) or quantitative surveys, while qualitative insights remain underexplored. Addressing these gaps, this study adopts a mixed-methods approach, combining an SLR with key informant interviews (KIIs) of industry professionals in Ghana—a region underrepresented in current research yet notable for its advancements in ICT adoption. Guided by the Task-Technology Fit (TTF) model and the Technology-Organization-Environment (TOE) framework, the SLR synthesizes findings from six reputable databases on the impact of AI on the project management body of knowledge (PMBOK) Guide, while KIIs provide contextual insights into practical challenges and opportunities. The research seeks to answer two primary questions: (1) How do AI-driven tools and techniques influence PM practices, including principles, process groups, and performance measures? (2) What challenges arise in implementing AI within PM in Ghana, Africa? Findings are expected to contribute theoretical and practical perspectives, offering actionable recommendations for organizations and future research directions (with four propositions). This study underscores AI's transformative potential in PM and highlights the need for integrative frameworks to guide its effective adoption.

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CHAPTER 1: INTRODUCTION

1.1 Background of the Study

Advancements in digital technologies are significantly transforming organizations and business operations. Among these, artificial intelligence (AI) has experienced rapid growth and is increasingly recognized as a disruptive force across various industries and sectors (Georgiev et al., 2024; Tominc et al., 2023). In recent years, organizations have adopted AI tools and techniques as part of their strategic plans to get ahead of the competition, especially in markets that are very fast-paced and competitive. For instance, Gartner (2025) forecasts that global spending on generative AI (GenAI) would reach $644 billion in 2025, which is a 76.4% increase from 2024.

AI functions as a transformative technology that enhances operational efficiency and facilitates organizational growth. Felicetti et al. (2024) indicate that AI is fundamentally transforming competitive dynamics by offering a strategic advantage to organizations that effectively incorporate the technology into their core business processes. This trend indicates the growing application of AI tools and techniques across diverse industries (Mahdi et al., 2020; Vergara et al., 2025) and business functions to improve operational performance. Project management is a critical business function.

Project management (PM) is the core organizational function responsible for the creation of unique products and services (Project Management Institute, 2021). It serves as a strategic instrument for executing company goals, generating organizational value, and achieving corporate objectives. Indeed, the performance and success of an organization are closely linked to the proper execution of its projects. In response to the growing global population, there is an increasing demand for infrastructure investments, accompanied by a projected rise in infrastructure development projects

to accommodate and sustain this demographic expansion (Datta et al., 2024). The integration of AI in critical company functions, such as project management, signifies a deliberate and purposeful choice intended to outperform competitors and get enhanced operational results.

Achieving successful PM outcomes with AI requires the identification of appropriate AI tools and techniques that align with specific PM activities or practices. Notably, certain AI tools and techniques may demonstrate greater effectiveness in particular PM areas than others. Consequently, empirical research is essential to examine which aspects of PM are being influenced by AI and to determine the specific tools and techniques contributing to these impacts. There has been an increasing scholarly interest in the application of AI to PM practices in recent years (Alam et al., 2025; Nenni et al., 2024; Prasetyo et al., 2025; Sarwar & Rahman, 2024; Tian et al., 2025; Vergara et al., 2025). Despite the growing interest, the current literature is deficient in a holistic and integrative study framework to comprehensively assess the influence of AI across the diverse areas of PM. For instance, previous research in this field has predominantly utilized singular methodological frameworks, with certain studies concentrating solely on SLRs (Prasetyo et al., 2025; Sarwar & Rahman, 2024; Tian et al., 2025), while others have utilized quantitative survey methods (Felicetti et al., 2024; Kineber et al., 2024). Furthermore, few researchers have employed design science research approaches (Fan, 2022; Sklias et al. 2024; Zeng & Gao, 2024), whereas fewer have utilized qualitative research using semi-structured interviews, such as that conducted by Kumar et al. (2022).

The combination of systematic literature reviews with qualitative interviews of industry experts, a methodology that could provide both theoretical richness and practical insight, remains inadequately explored in this field. Alongside the methodological gap, a significant geographical

gap exists in the current literature, with the majority of studies in this field concentrating on regions like Asia and Europe. Research on the application and impact of AI in PM remains limited in underdeveloped regions, highlighting the importance of extending research to countries in these regions.

1.2. Project Management Practices in Africa Context

Africa remains one of the underdeveloped regions in the world despite its vast natural resources. With the increasing investment in infrastructure projects, Africa has become one of the destinations of foreign investment. Also, diffusion of technology is relatively low, with many countries in Africa having limited access to digital technology, such as AI. The AfDB, African Development Bank Group (2025) forecasts that inclusive deployment of AI could generate up to US$1 trillion in additional gross domestic product (GDP) for Africa by 2035. Nonetheless, the AfDB report should not be interpreted as an automatic outcome of AI deployment; rather, it highlights the need to develop underlying digital infrastructure, institutional capacity, and AI skills, especially for project management applications.

Although project management is well established in advanced economies, its practice remains comparatively underdeveloped across much of Africa. Consequently, many African organizations, particularly multinational firms, have established project management offices (PMOs) and depend heavily on professionals sourced from more developed countries. Nonetheless, recent years have seen a shift: many public and private organizations are establishing PMOs oriented toward strategic project outcomes. For example, a 2022 joint study by the PMI and PricewaterhouseCoopers (PwC) reported that sub-Saharan Africa is rapidly growing its project economy, with more organizations relying on PMOs to manage complex projects. Moreover, the report highlighted the need for developing project management skills and the adoption of technology-enabled solutions for PM (Project Management Institute, 2022).

Furthermore, the report (Project Management Institute, 2022) recognized the expansion of project management structures across Africa, particularly through the establishment of PMI chapters in countries such as Ghana, Nigeria, Kenya, and South Africa. These chapters have facilitated professional development opportunities and fostered interest in PM certification programs. Amid

growing global complexity and uncertainty (Project Management Institute, 2025a), technology-enabled project management has become essential. Traditional project management information systems (PMISs) are being disrupted by AI integration, driving transformative changes in practices that necessitate organizational and professional adaptation (Hughes, Kiani, et al., 2025).

Scholarly discourse increasingly emphasizes that the integration of AI into PM practices is contingent upon the availability of robust technological infrastructure, particularly digital platforms (Kineber et al., 2024; Waqar et al., 2023). Several studies note that limited investment in such enabling systems across African countries constrains the pace of AI adoption (Ifeoma et al. 2025; PMI, 2025). At the same time, reports highlight Africa's potential to leverage AI for economic transformation through project-based initiatives, pointing to opportunities in efficiency gains and innovation (African Development Bank Group, 2025). According to Domor et al. (2024), noted that AI possesses considerable potential to drive sustainable development across Africa. However, this potential is tempered by a persistent skills gap (Domor et al. 2024; Ifeoma et al. 2025; PMI, 2025), with analyses underscoring the need for organizations to cultivate AI competencies to achieve the level of proficiency required for transformative outcomes. Collectively, these perspectives suggest that while Africa is well-positioned to benefit from AI-enabled PM, both infrastructural investment and workforce development remain critical prerequisites for realizing this promise.

1.3. Research Questions

In light of the noted gaps in the current literature and the current PM practices in Africa, coupled with the challenges of integrating AI, this study examines the influence of AI on project management, encompassing *processes, knowledge areas, and performance* domains. The study employs a mixed-methodology, integrating an SLR with key informant interviews of industry professionals from Ghana, to elucidate AI's involvement in modern PM methods. In order to conduct a comprehensive literature review of the impact of AI on PM practices and provide practical implications regarding the successful implementation of AI into PM practices in the African region, this current study seeks to answer the following research questions:

RQ1*:* How do AI-driven tools and techniques influence project management practices?

More specifically, this study will cover the following question: *How does the integration of AI-driven tools and techniques influence the project management principles (team, stakeholders, risk, complexity, quality, etc.), and performance domains (planning, development, project work, delivery, etc.), process groups (initiation, planning, execution, etc.)?*

In addition, the study aims to identify technological, organizational, and environmental challenges associated with the integration of AI into PM practices. To explore the challenges associated with implementing AI into PM practices, especially in the African regions, and provide some practical implications for these regions regarding the successful adoption of AI in PM practices, the following question will also be answered.

RQ2*:* What are the challenges of implementing AI-driven tools and techniques within project management practices in Ghana, Africa?

To answer these questions, the study uses a mixed-methods strategy that includes an SLR and qualitative interviews with industry professionals in Ghana. Based on theoretical perspectives of the Task-Technology Fit (TTF) model (Goodhue & Thompson, 1995) and the Technology, Organization, and Environment (TOE) framework (Tornatzky & Fleischer, 1990), the SLR involved evaluations of peer-reviewed articles and conference papers sourced from six reputable databases to systematically synthesize current findings on the impact of AI on PM. Also, the qualitative key informant interview (KII) consisted of semi-structured interviews with key informants from Ghana, including open-ended questions to extract comprehensive insights and contextual understanding (Creswell & Clark, 2018). Then, this study concludes with several

propositions for future research, integrating the findings from SLR and KII. Ghana is selected as an appropriate context for this study due to its leading position in Africa with respect to information and communication technology (ICT) infrastructure and the adoption of digital technologies (David & Grobler, 2020).

The remainder of this paper is structured as follows: the subsequent section defines key concepts and provides a classification of artificial intelligence technologies, along with an overview of project management practices, including processes, knowledge areas, and performance domains. Chapter 3 presents a detailed, step-by-step account of the methodology employed in the SLR segment of the study, followed by a synthesis of the key findings from SLR, focusing on the AI used for the Guide to the Project Management Body of Knowledge (PMBOK® Guide) Seventh Edition (PMBOK7) areas. Chapter 4 presents the methodological approach used for qualitative interviews with key informants, the key findings derived from the interview data, and several propositions after integrating the findings from SLR and KII. Chapter 5 will present the key academic and practical contributions derived from the research. Finally, the chapter will conclude the study by acknowledging its limitations and recommendations for future research.

CHAPTER 2: THEORETICAL BACKGROUND

2.1 Core Concepts, Classifications of AI Technologies, and Definitions

AI was first introduced in 1955 by John McCarthy and his colleagues during the Dartmouth Summer Research Project, where it was defined as the science of creating intelligent machines (McCarthy et al., 2006). Since its inception, AI has undergone significant evolution, encompassing a wide range of concepts, methodologies, and applications. The definition of AI differs across the literature, contingent upon the disciplinary or conceptual framework. For instance, Osamy et al. (2022) define AI as a significant branch of computer science aimed at making machines "smart." They describe AI as the capability of a computer system to perform tasks that typically require human intelligence, thereby mimicking human cognition and thought processes.

Fundamentally, AI refers to the capability of a computer program to reason, learn (Kineber et al., 2024), and adapt based on data and experience. Datta et al. (2024) describe AI as a dynamic and interdisciplinary field situated at the intersection of computer science, cognitive science, and mathematics. They define AI as the study and development of intelligent systems capable of exhibiting human-like intelligence, including reasoning, problem-solving, and decision-making abilities. Datta et al. (2024) find AI as a dynamic and interdisciplinary field at the intersection of computer science, cognitive science, and mathematics. According to Datta et al. (2024), AI is the study and development of intelligent systems with human-like intelligence, reasoning, problem-solving, and decision-making capacities. **Figure 1** illustrates the classification of AI, and **Table 1** provides definitions and explanations of these classifications.

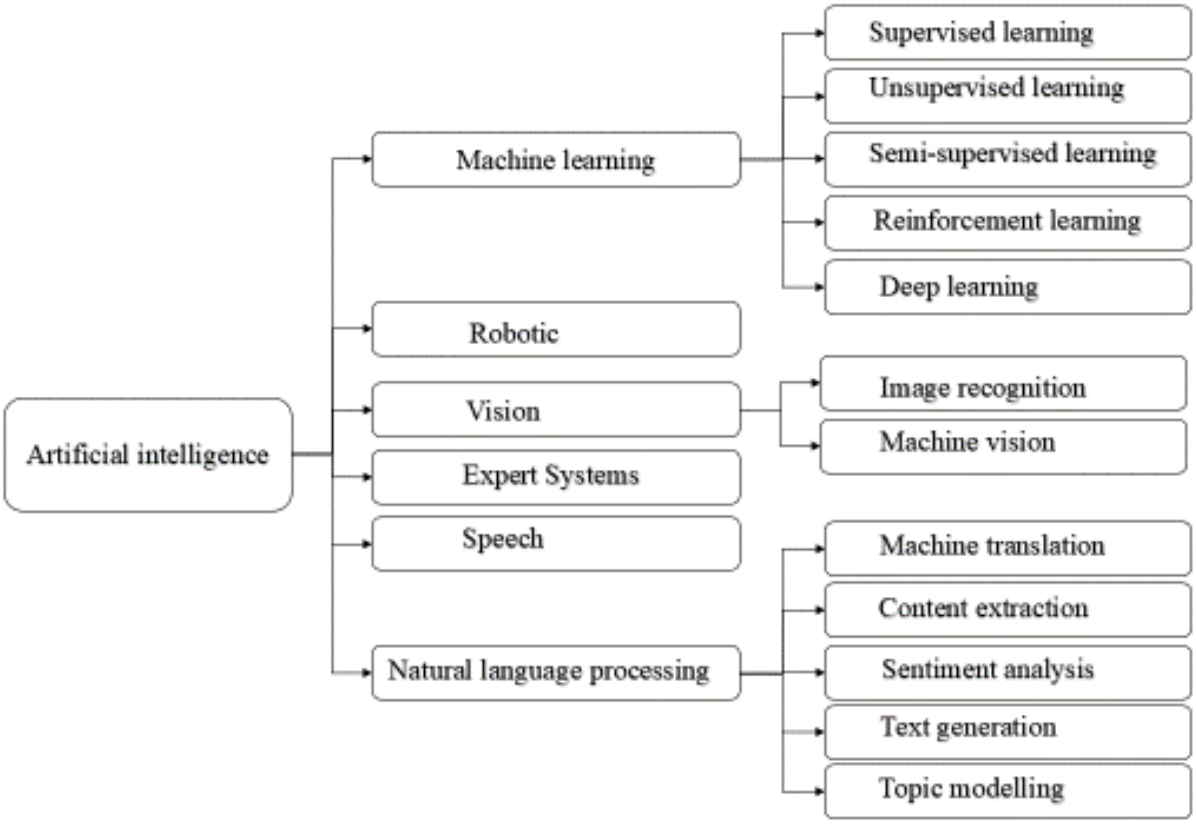

Figure 1 Classification of artificial intelligence

Table 1. Definition and explanation of key terms

Artificial Intelligence	**Explanation**	**Author(s)**
Machine Learning (ML)	Machine learning (ML) is a subfield of AI that focuses on the development of algorithms and models enabling machines to automatically learn from data, thereby enhancing performance through experience.	Datta et al. (2024), Prasetyo et al. (2025), Uysal & Akturk, (2024)
Supervised Learning	Supervised learning enables machines to make decisions based on labeled datasets containing input-output pairs.	Tian et al. (2025)
Unsupervised Learning	Unsupervised learning allows machines to discover patterns and underlying structures within unlabeled datasets.	Tian et al. (2025)
Reinforcement Learning (RL)	RL involves learning an optimal mapping between environmental states and corresponding actions to maximize a reward or reinforcement signal. (i.e., Learning through trial and error)	Tian et al. (2025); Kineber et al. (2024)

Artificial Intelligence	Explanation	Author(s)
Deep Learning (DL)	DL entails training deep neural networks composed of multiple layers to learn and recognize complex patterns within large datasets.	Tian et al. (2025); Datta et al. (2024)
Artificial Neural Networks (ANN)	ANNs, advanced forms of DL, are designed to solve complex problems by processing information received from external environments. ANNs are characterized as information processing systems that imitate the functioning of biological neural networks and are known as deep neural networks.	Fan (2022)
Natural Language Processing (NLP)	NLP is a technology that utilizes algorithms and models. NLP simply focuses on the interaction between computers and human language. NLP encompasses a broad set of techniques derived from both linguistics and ML. The primary focus of NLP is to enable computers to understand, interpret, and generate human language, thereby facilitating a practical understanding necessary for addressing complex problems	Tian et al. (2025); Craveiro & Domingues (2025)
Fuzzy Logic (FL)	FL is a mathematical framework that extends traditional Boolean logic. FL facilitates approximate rather than exact reasoning, enabling the representation and management of uncertainty and vagueness in decision-making processes. FL is another AI technique that emulates human decision-making processes. It is particularly effective in handling uncertain reasoning and managing incomplete or imprecise information.	Craveiro & Domingues (2025); Osamy et al. (2022)

2.2 Evolving Project Management Practices in Focus

The PMBOK (Project Management Book of Knowledge) Guide presents valuable standards, concepts, processes, and techniques for PM. While other frameworks, such as PRINCE2 (Projects IN Controlled Environments), exist, PMBOK remains the most widely accepted and frequently referenced guide (Fridgeirsson et al., 2021; Hashfi & Raharjo, 2023; Nenni et al., 2024; Uysal & Akturk, 2024) in both practice and research (Takagi & Varajão, 2020). Given this, the PMBOK Guide provides an important theoretical framework for this study. According to the Project Management Institute's (PMI's) PMBOK® Guide – Seventh Edition (PMBOK7, 2021), a project is defined as a temporary endeavor undertaken to create a unique product, service, or result. Project management, in turn, is described as the application of knowledge, skills, tools, and techniques to

project activities in order to meet specified project requirements. As global complexity and project-related expenditures continue to rise, the knowledge, skills, tools, and techniques required for effective PM are also evolving to keep pace with these developments. As a result, substantial modifications have been included in the PMI's PMBOK® Guide, especially during the transition from the 6th Edition (PMBOK6) to the 7th Edition (PMBOK7) in August 2021, demonstrating a concerted effort to synchronize project management methods with the evolving and increasingly complex project landscape.

The PMBOK6 identifies ten knowledge areas central to effective project management: integration, scope, schedule, cost, quality, resources, communications, risk, procurement, and stakeholder management (Fridgeirsson et al., 2021). On the other hand, the PMBOK7 takes a principle-based approach, introducing twelve guiding principles intended to support PM, strategic alignment, decision-making, and problem-solving. These principles are stewardship, team, stakeholders, value, systems thinking, leadership, tailoring, quality, complexity, risk, adaptability and resiliency, and change (PMBOK7, 2021). The PMBOK7, (2021) states that the application of the twelve principles is contingent upon context, shaped by elements including the organizational environment, the characteristics of the project deliverables, the nature of the project team, and stakeholder interests. The guide highlights the unique yet complementary nature of these concepts, indicating that they do not contradict each other but rather foster internal coherence within project management methods.

PMBOK6 delineates PM into five process groups: initiation, planning, execution, monitoring and controlling, and closing. In PMBOK7, the framework has transitioned from a process-based approach to an emphasis on project performance domains. PMBOK7 (2021) defines a project

performance domain as a collection of interrelated activities crucial for the effective delivery of project outcomes. The eight performance domains (Craveiro & Domingues, 2025) offer a comprehensive view of project performance. These domains encompass stakeholders, team dynamics, development approaches and life cycles, planning, project execution, delivery, measurement, and uncertainty (PMBOK7, 2021). This transition highlights a focus on comprehensive performance results instead of prescriptive process sequences. The domains are interrelated, interactive, and interdependent, working together to achieve the desired project objectives. The focus on project performance domains aims to create a framework of interrelated PM activities that together enhance value creation (Uysal & Akturk, 2024). **Figure 2** below shows the shift from former project management techniques to the present activities, emphasizing the evolution in accordance with contemporary PM frameworks and methodology.

Even after the shift to the PMBOK7 Guide, research continues based on the previous PMBOK6, concentrating on process groups (Hashfi & Raharjo, 2023) and knowledge areas (Fridgeirsson et al., 2021; Uysal & Akturk, 2024). Simultaneously, research is being conducted that analyzes the project management principles and performance domains outlined in the new guide (Craveiro & Domingues, 2025; Taboada et al., 2023; Uysal & Akturk, 2024). The persistent emphasis on the PMBOK6 Guide might be ascribed to the incomplete adoption of the 7th Edition by numerous organizations and PM practitioners. They are customizing their project management methods by choosing common (or corresponding) parts from both editions to align with their own organizational settings and project needs.

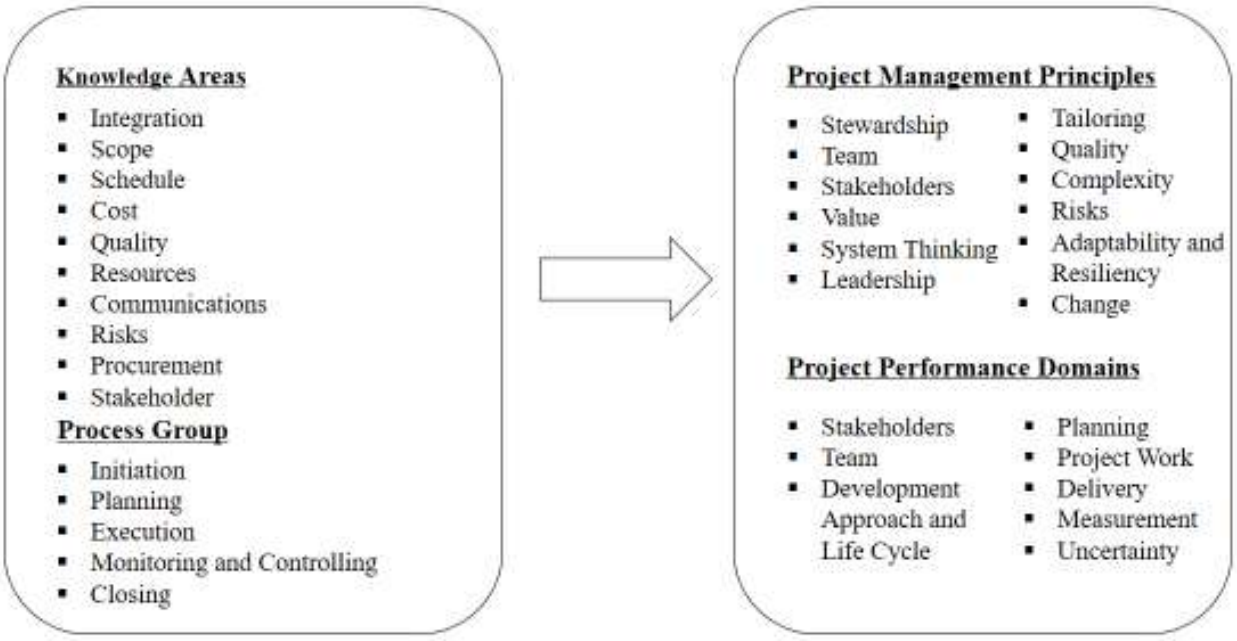

Figure 2 Structure of PMBOK 6th to 7th Edition: adapted from PMBOK7, (2021)

The increasing interest in the utilization of AI in project management (Sarwar & Rahman, 2024) is seen in both academic research and among industry professionals (Kumar et al., 2022). The PMI has recognized the strategic significance of using AI in project management to improve the attainment of effective project results. In response, PMI is actively pushing for an agenda that seeks to spearhead the AI-driven transformation of the profession, envisioning a future where AI capabilities complement human creativity (Hughes et al., 2025). PMI has included AI-related information into its project management training and professional development programs as part of this initiative. The PMIxAI eLearning platform (Project Management Institute, 2025) provides courses including “Practical Application of Generative AI for Project Managers,” “Generative AI Overview for Project Managers,” and “Prompt Engineering for Project Managers,” among others. Additionally, PMI Infinity™ has been introduced as an AI coaching tool to assist project managers in project delivery. These offers highlight the increasing focus on providing project managers with

the necessary skills to proficiently incorporate AI into the management of high-performing projects.

2.3. Overarching Theoretical Frameworks

The impact of technology adoption and its organizational challenges has been extensively examined through various theoretical lenses (Felicetti et al., 2024). The adoption of AI technologies, particularly within PM, is an emerging area of scholarly interest. Among existing theoretical frameworks that provide guidance for such inquiries, the study employed two theoretical frameworks, discussed below, to inform its investigation of the research questions, as I believe they fit the context of the PM industry adopting the newest technology (i.e., AI) for tasks in the fields.

2.3.1. RQ1: Task-Technology Fit

The Task-Technology Fit (TTF) model (Goodhue & Thompson, 1995) emphasizes that IT impacts performance only when effectively utilized and good fit to the tasks it supports. Indeed, the TTF is the degree to which technology supports individuals in performing a task (Goodhue & Thompson, 1995). Given this, the TTF framework recognizes important elements such as technology characteristics (AI tools, techniques, etc.), task characteristics (PM activities, tasks, etc.), and the characteristics of the individual (technical skills, motivations, etc.) (Goodhue & Thompson, 1995). Following Felicetti et al. (2024), who applied TTF to project managers' integration of GenAI, the TTF model underpins this study by linking specific AI solutions (e.g. ChatGPT, Copilot, ANN, etc.) to their use in PM activities such as planning, scheduling, cost estimation, resource allocation, and others. Moreover, Goodhue & Thompson (1995) note that individuals' behavior in utilizing technology to perform tasks is critical within the TTF model for

achieving optimal outcomes. Therefore, the theoretical perspective of TTF provides a framework for aligning different types of AI-driven tools with specific project management tasks and knowledge areas, thereby addressing Research Question 1: the impact of AI-driven tools and techniques on project management practices.

2.3.2. RQ2: Technology, Organization, and Environment (TOE) Framework

The Technology, Organization, and Environment (TOE) framework (Tornatzky & Fleischer, 1990) highlights how technology, organization, and the external environment interact to shape technology adoption and use. Tornatzky & Fleischer, (1990), noted that technological, organizational, and environmental characteristics can present both opportunities and barriers to the adoption of new technology (Faiz et al., 2024). Given this, the TOE framework is employed in this study to examine challenges in implementing AI-driven tools within PM (research question 2), analyzing organizational adoption of AI technology through internal and external factors (Mohammad & Chirchir, 2024), including IT infrastructure and technology readiness (Ayinaddis, 2025). The TOE framework also considers organizational resources and capabilities, and environmental contexts, such as market trends and regulatory policies (Mohammad & Chirchir, 2024). Overall, challenges in integrating AI into PM are categorized as technological, organizational, and environmental.

CHAPTER 3. STRUCTURAL LITERATURE REVIEW

The SLR followed a hybrid approach that integrates the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines and the CEBMa Guideline for Rapid Evidence Assessments in Management and Organizations (Barends, E; Rousseau, D.; Briner, 2017). The methodology aligns with established practices in prior research conducted by Ain et al. (2019), Lee et al. (2024), Salimimoghadam et al. (2025), and Tian et al. (2025), thereby enhancing the credibility and comparability of the review findings.

3.1 Systematic Literature Process

The SLR in this study began by developing a protocol to ensure openness and reduce potential bias (Lee et al., 2024; Tian et al., 2025). A well-defined protocol for conducting an SLR improves the replicability of the study (Salimimoghadam et al., 2025) and ensures compliance with established guidelines and methodological frameworks. After the establishment of the review protocol, the study advanced through the methodological steps depicted in ***Figure 3***. The process involved formulating a thorough literature search strategy, subsequently applying predefined inclusion and exclusion criteria to evaluate the relevance of the identified research articles. A backward citation search was conducted by reviewing the reference lists of initially selected studies to identify additional relevant sources before finalizing the set of articles for analysis. The selected articles for inclusion underwent a structured data extraction process, followed by systematic analysis and synthesis of the data. The final stage entailed the identification and discussion of key insights and findings derived from the synthesized evidence.

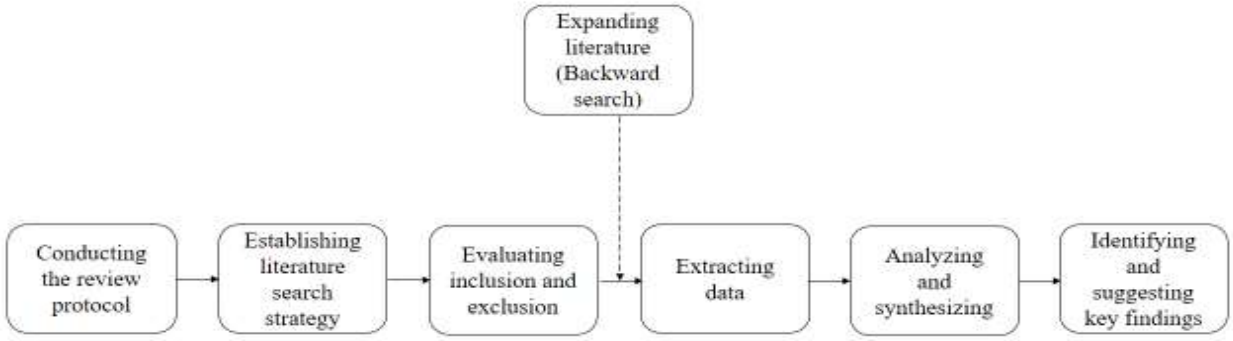

Figure 3. *Research methodological steps*

3.2 Literature Search Strategy

A systematic literature search strategy was employed to gather existing knowledge regarding the impact of AI on project management practices. This strategy entailed the systematic identification and selection of academic databases that could supply pertinent literature to address the research questions presented in the previous section. The choice of databases was guided by the interdisciplinary characteristics of the research topic, encompassing two main areas: AI and PM. The literature search was performed across six prominent academic databases recognized for their comprehensive coverage of these disciplines: ABI/INFORM, Business Source Complete, Scopus, ScienceDirect, IEEE Xplore, and Google Scholar.

The study established a set of search terms pertinent to the research topic, which were subsequently refined into keywords to improve the identification of relevant academic sources. Initial keywords encompassed "artificial intelligence" and "project management practices". The scope was broadened and relevant literature comprehensively covered by extending and refining these keywords using Boolean operators. The Boolean operator "OR" was utilized to include synonymous or related terms, thus broadening the search scope.

For example, the search strategy utilized complex search strings, including: (artificial intelligence OR AI OR machine learning OR ML) AND (project management OR project risk OR project leadership OR project scope OR project cost OR project budget OR project schedule OR performance domain). This method facilitated the acquisition of a comprehensive and representative collection of publications pertinent to the study's aims. The study used a customized search strategy, utilizing specific search strings for each literature database. This method aims to enhance the retrieval of relevant articles by considering the distinct indexing systems, search functionalities, and subject coverage of each database (Tian et al., 2025).

3.3 Inclusion and Exclusion Criteria

Inclusion and exclusion criteria were defined at the beginning of the study to provide a systematic framework for the selection of relevant research. The criteria were defined to establish the scope and boundaries of the literature search, ensuring that only studies directly relevant to the research objectives were included. ***Table 2*** outlines the specific inclusion and exclusion criteria utilized in the study. The selected search period of 2020 to 2025 aims to incorporate suitable and current studies that illustrate the evolving practices in project management, particularly those consistent with the principles and performance domains outlined in PMBOK7 (PMBOK7, 2021). This period encompasses the latest developments, advancements, and emerging trends in the integration of AI into project management practices. The inclusion criteria primarily emphasized peer-reviewed journal articles and conference proceedings; however, the study also referenced important non-peer-reviewed sources and grey literature for emphasis. Grey literature comprises non-peer-reviewed papers and professional reports (e.g., Gartner reports, Statista reports, government reports, etc.). The inclusion of such materials was intended to capture current trends and practical

developments within the professional environment, thereby complementing the academic literature with real-world insights.

Table 2. Inclusion and exclusion criteria

Inclusion Criteria	Exclusion Criteria
▪ Studies published between 2020 to 2025 ▪ Project management practices involving *the process group, knowledge areas, project management principles, and performance domain*, with *the focus on artificial intelligence* ▪ Peer-reviewed articles and conference papers ▪ Articles published in English ▪ 6 Selected databases ▪ Quality assurance criteria not less than 3.5 (Table 3)	▪ Studies published before 2020 ▪ Studies outside the domain of project management and AI ▪ Non-peer-reviewed journal articles ▪ Articles not published in English ▪ Duplicates ▪ Quality assurance criteria less than 3.5

3.4 Study Selection Process

The study selection process was guided by the flowchart recommended in the CEBMa Guideline for Rapid Evidence Assessments in Management and Organizations (Barends, E; Rousseau, D.; Briner, 2017). **Figure 4** served as a structured documentation tool, outlining the key steps involved in identifying, screening, and selecting studies for inclusion. Consistent with the CEBMa recommendations, the flowchart enhanced transparency and reproducibility in the study selection process.

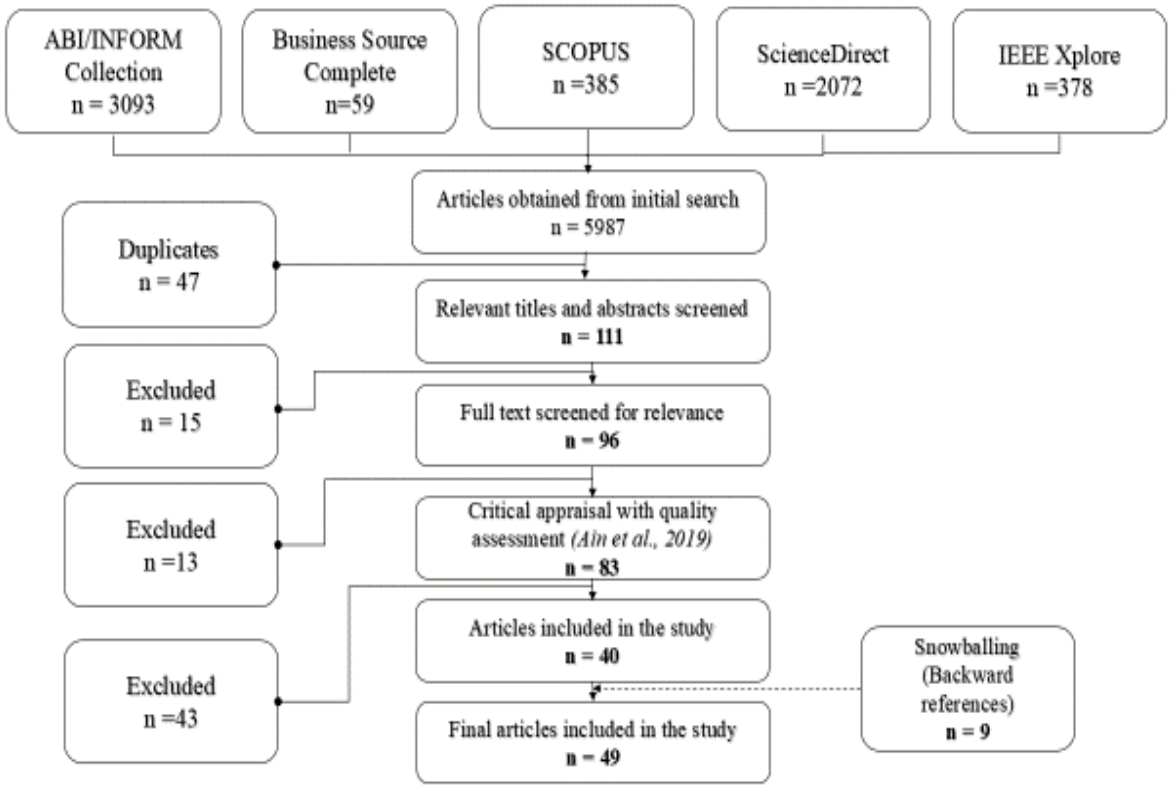

Figure 4 Flow chart of the literature selection process

The initial search, conducted using the predefined keywords and search strings outlined in the preceding section, was applied across five electronic databases: ABI/INFORM, Business Source Complete, Scopus, ScienceDirect, and IEEE Xplore. This search yielded a total of 5987 records. Following the retrieval of the initial set of articles, a screening process was undertaken to identify studies relevant to the research focus on AI and PM, as defined by the inclusion criteria. In the initial stage of the screening process, 47 duplicate records identified across the five databases were removed, resulting in a refined set of 111 unique articles eligible for further review. The next step of screening involved a review of article titles and abstracts to assess their alignment with the study objectives. As a result of this process, 96 articles were identified as meeting the basic inclusion criteria and were also selected for further evaluation. The process that followed was to read the

full text of all 96 articles for relevance to the study in terms of the research questions and objectives of the study. This stage of the screening process resulted in the identification of 83 relevant articles deemed suitable for inclusion in the SLR. An additional screening phase was undertaken, involving a critical appraisal of the remaining articles using established quality assessment criteria. Specifically, the study applied five quality assessment questions adapted from (Ain et al., 2019), as outlined in ***Table 3.***

Table 3. Quality assessment criteria

Question	Score (0-1)
1. Does the research topic pertain to AI in relation to project management?	
2. Is the context of the research clear?	
3. Does the research adequately delineate the methodology?	
4. Is the data collection procedure adequately explained?	
5. Is the approach used for data analysis appropriately explained in the research?	
TOTAL	

Based on the above quality assessment criteria, each question was evaluated using a ranking scale, with 'High,' 'Medium,' and 'Low' assigned numerical values of 1, 0.5, and 0, respectively. In this context, articles with a total score equal to or greater than 3.5 were classified as high quality and included in the analysis. Articles that received a quality assessment score of 3 or lower were excluded from the final analysis. Tian et al. (2025) utilized a similar set of quality assessment criteria in their SLR. Their findings indicate that the inclusion of an evaluation process improves the reliability and validity of research outcomes by guaranteeing that only methodologically sound and relevant studies are part of the final synthesis. A total of 40 research articles met the established

methodological standards following the application of the quality assessment criteria outlined above and were included in the study. As a result, 43 articles were excluded at this stage for not meeting the specified quality evaluation criteria. During the final stage of the review process, a manual backward search was performed utilizing a snowballing technique to verify the comprehensiveness of the systematic literature search (Ain et al., 2019; Lee et al., 2024). This method entailed a manual review of the reference lists from the initially selected studies within the Google Scholar database to identify further relevant literature. The articles obtained via the backward snowballing method underwent the same screening and quality assessment protocols outlined in the flowchart in **Figure 4**. Consequently, an additional 9 research articles satisfied the quality assessment criteria, resulting in a total of 49 relevant articles included in the final review.

3.5 Data Extraction and Synthesis Processes

After the selection of the final 49 research articles for inclusion, the study proceeded with a systematic data extraction process. This critical step facilitates the adequate synthesis and analysis of the results and findings presented in the selected studies. To support this process, a structured data extraction table was developed using a Microsoft Excel spreadsheet and is presented as Appendix II to this document. The table was designed to capture elements that are both relevant and aligned with the specific objectives of the study. These elements comprised: *author(s) of the study, year of publication, article title, industry context, geographical location (country or region) where the study was conducted, PM practices referenced in accordance with PMBOK guidelines, theoretical or conceptual framework employed, research method (data collection), research method (data analysis), reported results, key findings, and additional comments or observations relevant to the study*. Each article was subjected to a thorough content review, during which

relevant data were systematically extracted and populated into the data extraction table, as outlined in Appendix II. The extracted information corresponded to the predefined elements developed to ensure consistency and relevance in alignment with the study's objectives.

3.6 Results and Findings from the Systematic Literature Review

3.6.1. Historical Distribution

Data analysis was performed following the data extraction process outlined in the preceding section. The study utilized descriptive and narrative analytical methods to systematically analyze the retrieved data, enabling the identification of trends seen in the selected articles. The analysis indicated a significant rise in scholarly interest in the application of AI to PM practices beginning in 2020. Specifically, 2024 yielded the greatest number of articles, constituting around 37% of the 49 papers incorporated in the review. Notably, although the search occurred in mid-2025, almost 22% of the chosen articles had been published in the first half of the year. These findings indicate an increasing academic emphasis on the intersection of AI and PM in recent years. (Aladag et al., 2024; Vergara et al., 2025).

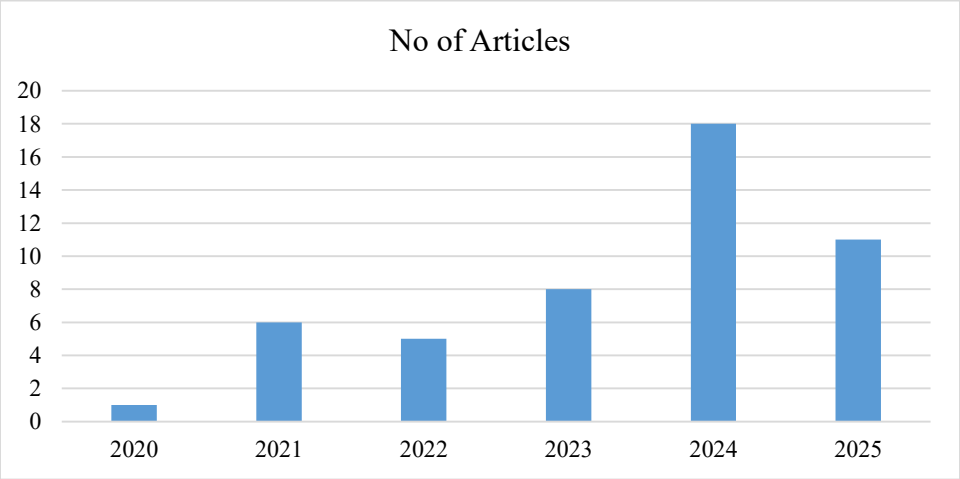

Figure 5. Number of papers published (2020-2025)

3.6.2. Geographical Distribution

In terms of geographical distribution, approximately 45% of the reviewed articles did not specify a particular regional focus, representing the largest category. This may be attributed to the large number of studies utilizing SLR. **Figure 6** illustrates the geographical distribution of the reviewed articles, categorized by respective regions. Among those with a defined regional context, Asia accounted for the highest number, with approximately 24% articles (Alam et al., 2025; Zeng & Gao, 2024), followed by Europe with approximately 20% articles (Nyqvist et al., 2024; Sklias et al., 2024). Surprisingly, the African region exhibited one of the lowest levels of research activity on AI applications in PM, with only 4% studies identified (Elmousalami, 2021; Kineber et al., 2024). The lack of academic research on the integration of AI and PM in Africa makes Ghana an even better choice for the qualitative part of this study. Interviewing industry experts in Ghana offers a chance to produce country-specific insights and help fill the geographical gap in the current situation, and offer practical implications for other nations across the continent.

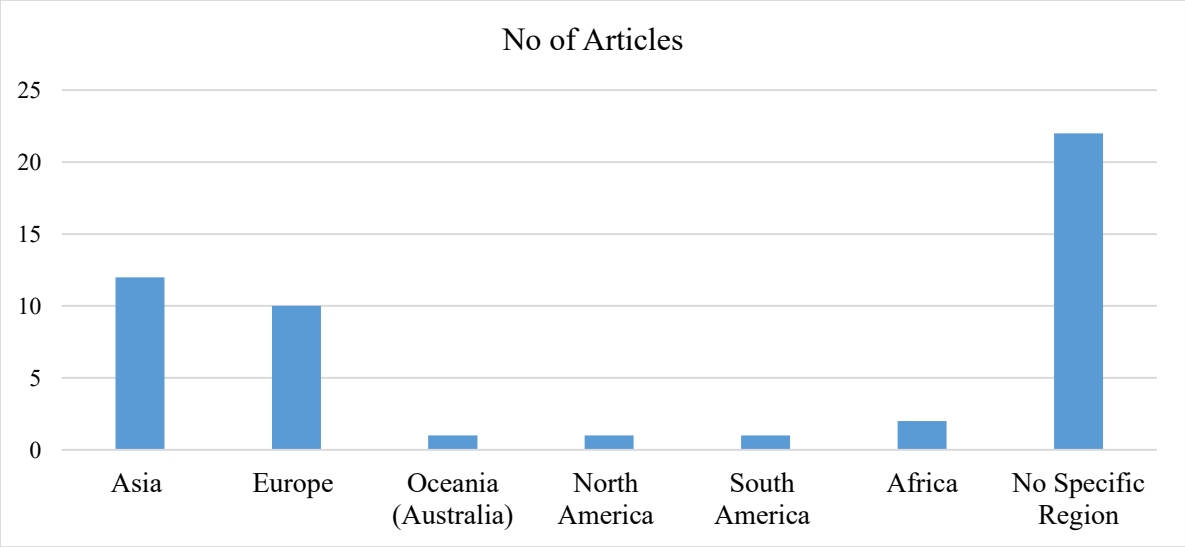

Figure 6. Articles presentation by geographical regions

3.6.3. Industry Distribution

AI has become an essential digital technology, demonstrating extensive applicability across multiple industrial sectors (Dimcheva, 2024; Prasetyo et al., 2025). The review's findings indicate that AI adoption in project management is unevenly distributed, with certain industries exhibiting markedly higher levels of application than others, as illustrated in ***Figure 7***. The analysis indicates that the construction industry demonstrates the greatest degree of AI application in project management, representing roughly 31% of the reviewed studies (Datta et al., 2024; Jing et al., 2025; Tian et al., 2025). Subsequently, research that either maintains a generic focus or lacks specification of a particular industry constitutes approximately 29% of the total articles (Adamantiadou & Tsironis, 2025; Felicetti et al., 2024). Furthermore, IT, software development, and telecommunications projects represent a considerable portion, accounting for roughly 27% of the analyzed literature, which suggests notable involvement with AI in these fields (Das et al., 2025; Dimcheva, 2024). These results align with broader industry trends, confirming substantial global investment in infrastructure development and the growing expenditure on IT. This observation is consistent with projections by Gartner (2025), which predicted a significant increase in IT spending worldwide in 2025. Surprisingly, despite the widespread view of advanced AI adoption within the healthcare sector, particularly healthcare innovations (Vaghasiya et al., 2025), the systematic review found that PM applications of AI in this domain were minimally represented. Specifically, healthcare-related projects accounted for only approximately 4% of the total research articles included in the study (Uysal & Akturk, 2024; Vaghasiya et al., 2025).

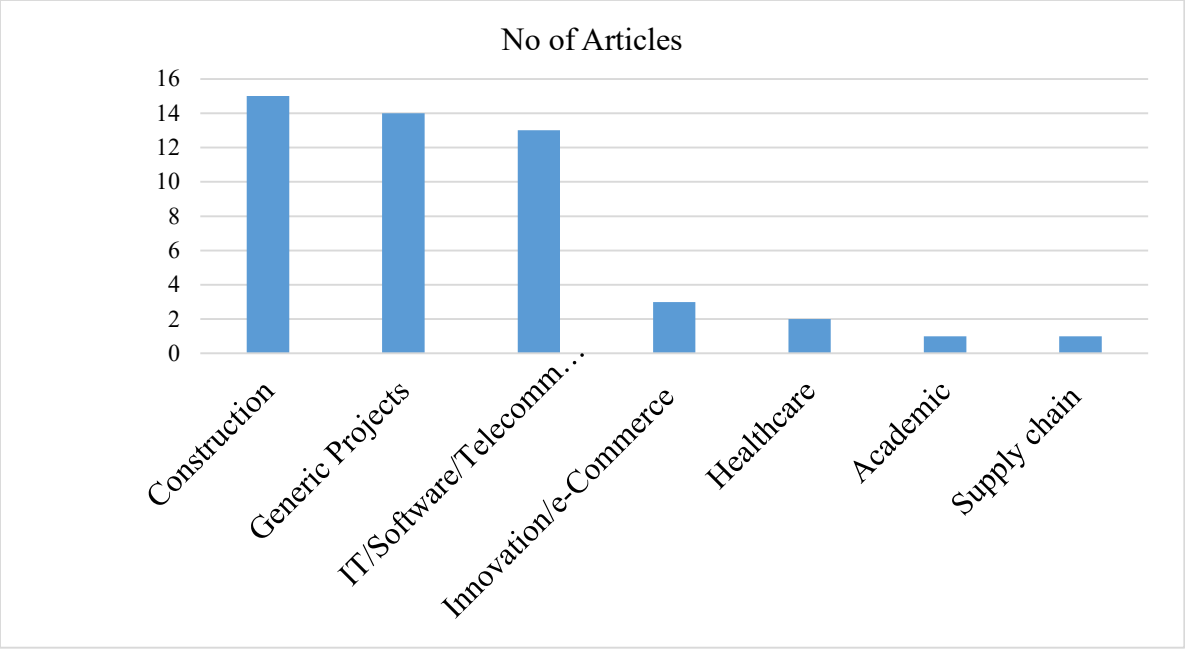

Figure 7. Research articles represented by industrial sectors

3.6.4. Research Methods Applied

As academic interest in the application of AI solutions in PM practices continues to grow, a diversity of methodological approaches has emerged. The findings indicate a strong preference for SLRs utilizing archival data, with 19 out of the 49 reviewed studies, representing approximately 39%, employing this methodology, as detailed in Table 4 below. Survey-based research emerged as the second most employed methodological approach, accounting for approximately 20% of the reviewed articles. Among these, 50% utilized Partial Least Squares-Structural Equation Modelling (PLS-SEM) as the primary technique for data analysis (Felicetti et al., 2024; Jing et al., 2025), indicating a preference for advanced statistical modelling within survey-based studies.

The findings also indicate a growing interest in the application of design science research in the study of AI within PM practices. Design science research accounted for approximately 14% of the

reviewed articles, making it the third most frequently employed methodological approach. Further analysis revealed that design science research was primarily utilized for ML model development and the application of ML algorithms (Uddin et al., 2022; Zeng & Gao, 2024) to address specific PM activities. Within these studies, data analysis techniques commonly included model and feature testing, with Root Mean Square Error (RMSE) frequently used as a performance evaluation metric (Choi et al., 2021; Sklias et al., 2024).

Although only 8% of the reviewed studies employed a mixed-methods approach (Bandara & Wickramaraawan, 2025; Shang et al., 2023), there is evidence of growing interest in alternative methodologies, such as case studies (Uddin et al., 2022; Yazdi et al., 2024), and experimental design research (Chan & Li, 2024; Nyqvist et al., 2024), each accounting for 6% of the reviewed articles. These findings support the methodological orientation of the present study, which adopts a mixed-method design by integrating an SLR with qualitative interviews.

Table 4. Methodological approaches to the research articles

Data Collection	No of Articles
Archival data (Systematic Literature Review)	19
Survey	10
Case Study	3
Design science research	7
Experimental design research	3
Mixed Method	4
Qualitative research	2
Secondary data (PMIS dataset)	1

3.6.5. PMBOK Areas

As conceptualized in Chapter 2, the PMBOK® Guide Sixth Edition categorizes project management activities into knowledge areas and process groups, whereas the Seventh Edition adopts a revised framework comprising project management principles and performance domains.

Among the 49 research articles reviewed, only a limited number explicitly focused on the core classifications of PM activities as outlined in the PMBOK® Guides. Specifically, 3 studies examined the knowledge areas (Fridgeirsson et al., 2021; Georgiev et al., 2024; Sarwar & Rahman, 2024), while another 3 addressed the process groups (Bandara & Wickramaraawan, 2025; Dimcheva, 2024; Georgiev et al., 2024). In contrast, only two studies focused on the performance domains introduced in the PMBOK7 (Taboada et al., 2023; Uysal & Akturk, 2024).

The application of AI in PM practices is primarily targeted at specific PM activities with the aim of enhancing efficiency and supporting the achievement of project objectives. As shown in ***Table 5***, the review revealed that research on AI tools and techniques tends to concentrate more heavily on certain PM activities than others, indicating areas of higher interest and applicability within the field. For example, the review identified risk management as the most extensively researched area in relation to the application of AI within PM activities. This finding aligns with the observation that a substantial proportion of AI-related PM research originates from the construction industry, where effective risk management is critical due to the complexity and uncertainty inherent in large-scale infrastructure projects. Infrastructure projects, particularly those within the construction sector, are widely recognized as high-risk undertakings. As noted by Okudan et al. (2021), such projects are especially susceptible to external conditions and project-specific uncertainties, which necessitate robust risk management practices supported by advanced analytical tools, including AI.

Following risk management, cost management and budgeting emerged as the next most frequently addressed PM activities in the reviewed literature (Prasetyo et al., 2025; Shamim et al., 2025). The analysis indicates that these areas have received substantial attention in studies exploring the application of AI in PM. This emphasis is understandable, given that cost constitutes one of the

three components of the PM triple constraints, namely scope, cost, and time (Noteboom et al., 2023), which are widely recognized as fundamental determinants of project success. As such, effective cost management is critical to achieving project objectives and overall performance. Several of the reviewed articles addressed PM in general terms or a non-specific context, without reference to particular activities (Cancer et al., 2023; Felicetti et al., 2024). Time management emerged as the next most frequently examined specific PM activity (Das et al., 2025; Siddiqa et al., 2024). Time management, as noted by Noteboom et al. (2023), also represents one of the core components of the PM triple constraints, alongside cost and scope, which are widely used as key indicators for assessing project success. Consequently, the critical role of time management in determining project success has attracted considerable attention from both practitioners and researchers, driving efforts to enhance project scheduling through the adoption of AI tools and techniques within PM practices.

Project planning (Datta et al., 2024; Mohammad & Chirchir, 2024) and resource management (Jayaram et al., 2024; Zeng & Gao, 2024) followed time management as the next most frequently examined PM activities in relation to the application of AI in this review. Each of these areas appeared in seven of the reviewed articles, indicating sustained scholarly interest in how AI can support the optimization of planning processes and effective allocation of project resources. The review yielded a surprising finding, indicating that project execution (Bandara & Wickramaraawan, 2025; Fan, 2022) and communications (Alam et al., 2025; Das et al., 2025) were among the least studied PM activities impacted by the application of AI tools and techniques. Specifically, project execution was addressed in only three of the 49 reviewed articles, while communications appeared in merely two studies, highlighting a potential gap in the literature regarding AI's influence in these critical areas.

Table 5. Research articles based on project management activities

Project Management Areas	No. of research articles
Risk management	13
Cost/Budgeting	10
Time/Scheduling	8
Planning	7
Resource	7
Communications	2
Execution	3
Outcome/performance	2
Team	1
Project Management (Generic)	9

3.6.6. Artificial Intelligence Types

As presented in **Table 6**, the results of the review revealed significant insights into the types of AI tools and techniques utilized in project management practices. Of the 49 research articles reviewed, 15 specifically focused on generic AI technologies, representing the largest category, while 4 articles concentrated on general ML technologies. The review identified a substantial focus on combined AI/ML technologies, which were addressed in 10 of the reviewed studies. Additionally, 11 articles specifically examined various ML models and algorithms, making this the third most represented category of AI tools in the dataset. Notably, the use of GenAI technologies in PM practices emerged as a significant trend, appearing in 13 articles. Among these, seven studies employed ChatGPT, three utilized Copilot, and the remaining three focused on the application of chatbots.

Table 6. Artificial intelligence tools and techniques

AI Tools and Techniques	No of Articles
AI Technology (Generic)	15
ML (Generic)	4
AI/ML	10
GenAI (ChatGPT)	7
GenAI (Copilot)	3

AI Tools and Techniques	No of Articles
GenAI (Chatbots)	3
ML models/algorithms	11

3.7. Mapping of AI Tool/Technique to PMBOK Areas

Corresponding to the theoretical perspectives of the TTF model (Goodhue & Thompson, 1995), this SLR indicates that particular types of AI are specifically effective for certain PM tasks. Synthesizing the findings from SLR, which addresses research question 1, ***Table 7*** presents a mapping of AI tools and techniques to the PM areas they support. The findings suggest that large language models (LLMs), particularly GenAI such as ChatGPT, chatbots, and Copilot, demonstrate strong effectiveness for repetitive PM tasks. Specifically, chatbots and Copilot have been shown to automate text-based processes and to provide real-time interactive support for stakeholders and project teams (Bandara & Wickramaraawan, 2025; Felicetti et al., 2024). ChatGPT demonstrates efficient performance in risk-management scenarios and, when combined with human judgment (Yazdi et al., 2024), contributes to the development of robust project plans. Effectively, LLMs facilitate decision-making processes in PM. Notwithstanding these positive impacts, the LLMs exhibit weak effectiveness for cognitively demanding tasks such as scheduling and cost estimation.

Moreover, the SLR found that ML models appear to mitigate the limitations of LLMs for cognitively demanding PM tasks and generally demonstrate superior performance in predicting and forecasting project-related functions. ANNs and ML techniques such as fuzzy logic, SVM, and random forest have demonstrated superior performance in schedule and cost prediction and estimation (Lishner & Shtub, 2022; Shamim et al., 2025). Additionally, ANNs and fuzzy logic have demonstrated effectiveness in risk management and also support resource management

functions, whereas SVMs are recognized for accurately classifying project functions such as schedule, cost, execution, and delivery (Fan, 2022).

These findings underscore the increasing integration of GenAI technologies and ML models in contemporary PM activities, as well as the challenges organizations face when implementing AI solutions. Therefore, the following sections focus the discussions on these findings.

Table 7. Mapping AI tools and techniques to PMBOK areas

PMBOK7 Areas/AI Tools	LLMs (GenAI)			Deep Learning	ML Models		
	ChatGPT	**Chatbots**	**Copilot**	**ANN**	**Fuzzy logic**	**SVM**	**Random Forest**
Schedule				Effectively predicts project duration	Prioritizes tasks and forecasts activity durations.	Accurate classification of schedule risk	
Cost		Automates and accelerates budget queries		Accurate cost estimations	Accurate cost estimations	Accurate classification of project costs	Forecasts spending trends and cost overruns
Resource	Efficiently forecasts resource needs and recommends optimal allocations				Efficient distribution of project resources		
Communications			Automates communication workflows				
Risks	Enhances risk assessment by rapidly producing detailed analyses for early detection, scenario analysis, and timely mitigation	Provides alerts on risk queries		Accurate project risk prediction	Accurate risk forecasts and robust response mechanisms		
Initiation			Automates initiation templates				

PMBOK7 Areas/AI Tools	LLMs (GenAI)			Deep Learning	ML Models		
	ChatGPT	**Chatbots**	**Copilot**	**ANN**	**Fuzzy logic**	**SVM**	**Random Forest**
Planning	Combines ChatGPT-4 with human judgment to enhance the robustness, reliability, and trustworthiness of project plans.	Automate project planning tasks	Consolidates project plans				
Execution			Automates execution monitoring	Forecasts execution progress		Classifies execution progress and outcomes	
Monitoring and Controlling		Automates data collection and tracking	Automates KPI dashboards for effective reporting				
Closure			Automates project closure documentations				
Team	Optimizes team composition and collaboration through personality and role analysis						
Delivery				Predicts delivery performance		Classifies delivery progress and outcomes	

3.8. Applications of GenAI in Project Management Practices

This analysis found that GenAI is the most commonly used AI tool and technique in PM publications, after generic AI and ML. The Gartner Report (2025) predicts that global spending on GenAI technologies would reach $644 billion in 2025, showing GenAI's growing importance and widespread usage across industries, including PM.

Bandara & Wickramaraawan (2025) applied GenAI tools, including ChatGPT, Copilot, Chatbots, and Power BI in PM process groups (Initiation, planning, execution, monitoring, closing) in software development projects. They found that many PM platforms have been integrated with GenAI in-built prompts features, such as ChatGPT and Copilot, to improve functionality and user engagement. Their findings showed that ChatGPT and Copilot assist with developing project plans, while Chatbots automate data collection and track engagement among stakeholders. Power BI also generates final reports during project completion, improving decision-making and reporting.

GenAI is revolutionizing PM by redefining cognitive activities and improving operational efficiency (Felicetti et al., 2024; Georgiev et al., 2024; Tian et al., 2025). Felicetti et al. (2024) discovered that tools such as ChatGPT and chatbots improve decision-making and optimize PM processes. Their study emphasized that peer influence plays a major role in AI adoption, and that effective implementation significantly relies on a strong task-technology fit, wherein project managers view the tools as appropriately aligned with their unique jobs.

AI, particularly GenAI, is widely used in PM to automate repetitive PM tasks (Alam et al., 2025; Dimcheva, 2024; Prasetyo et al., 2025; Sarwar & Rahman, 2024), boosting efficiency and freeing managers to focus on strategic functions. Studies show that chatbots, powered by advanced AI and NLP, streamline PM processes by minimizing manual intervention (Alshaikhi & Khayyat, 2021).

GenAI tools can act as virtual project managers, maintaining continuous communication with teams and stakeholders across time zones. This automation enables project managers to have greater attention to high-level cognitive tasks such as planning, problem-solving, and decision-making (Vergara et al., 2025), reinforcing GenAI's transformative role in modern PM practices.

Numerous scholars argue that GenAI tools outperform traditional human interventions in project PM. Nyqvist et al. (2024) in their experimental study compared human-generated and ChatGPT-produced risk management plans in a construction project. ChatGPT scored significantly higher (8.6 vs. 5.7) in peer reviews, praised for its comprehensive analysis but criticized for its limited practicality. The study highlights ChatGPT's superior data processing and risk identification capabilities, while human experts excelled in contextual and tacit knowledge. Yazdi et al. (2024) reinforced these findings, showing that GenAI tools like ChatGPT-4 deliver faster, more relevant insights, though human experts remain stronger in holistic and comprehensive assessments.

Similarly, the work by Jayaram et al. (2024) confirmed the effectiveness of ChatGPT in PM, showing that prompt engineering with ChatGPT-3.5 improved resource forecasting and allocation using historical data and predictive analytics. This approach reduced project risks and improved efficiency. Additionally, Barcaui & Monat, (2023) noted that both human-generated and AI-generated plans possess unique strengths and weaknesses. Moreover, Yazdi et al. (2024) acknowledged that GenAI tools struggle with contextual interpretation. Therefore, they advocate a hybrid approach, combining human judgment with AI capabilities to produce project plans that are more robust, contextually grounded, and operationally effective.

Recent studies show that project management information systems (PMIS) increasingly integrate AI to boost performance. Platforms like Asana (Bandara & Wickramaraawan, 2025; Hosseini & Seilani, 2025), Jira (Jayaram et al., 2024; Mohammad & Chirchir, 2024), and Monday.com (Das

et al., 2025) support real-time tracking, predictive analytics, and resource allocation, improving timelines and outcomes. Das et al. (2025) found that different PM platforms excel in distinct areas, with some outperforming others in executing specific PM tasks. For instance, Jira excels in dynamic resource allocation, Monday.com in real-time monitoring and automation, and Asana in collaboration and task tracking. These differences highlight the need to align platform capabilities with specific project requirements to maximize effectiveness and ensure optimal project execution.

3.9. Applications of ML Models in Project Management Practices

With rising interest in AI for PM, recent studies increasingly focus on developing ML models tailored to PM challenges. Research using design science, experimental, and case study methods aims to test and refine AI-driven solutions (Choi et al., 2021; Fan, 2022; Sklias et al., 2024; (Uddin et al., 2022). Shamim et al. (2025) found deep learning and hybrid models achieve up to 90% accuracy in cost estimation across sectors like construction and healthcare.

Shamim et al. (2025) also found Support Vector Machines (SVMs), Random Forest (RF), Gradient-Boosted Trees (GBT), and Extreme Gradient Boosting (XGBoost) as high-performing ML techniques in PM, while traditional models remain effective for specific tasks. Elmousalami, (2021) evaluated 20 ML models using data from Field Canals Improvement Projects, assessing cost estimation accuracy. The study found XGBoost emerged as the top performer, confirming its superior predictive capability in real-world PM contexts.

Indeed, ML model performance in PM varies by task, with each model performing in specific areas. Fan (2022) found SVM achieved 85.32% accuracy for cost and 79.01% for progress prediction, while ANN reached 93.20% for engineering level classification. For risk management, (Okudan et al., 2021) highlighted the CBrisk tool, a web-based system using fuzzy linguistic variables, as highly effective in handling uncertainty and imprecision in risk assessment processes,

delivering reliable results when provided with high-quality input data. A similar ML model, Engineering Machine-learning Automation Platform (EMAP), by Choi et al. (2021), found the platform to support risk management in project lifecycles, helping prevent errors and improve task accuracy.

AI has positively impacted PM by enhancing efficiency and decision-making. Design science researchers continue to advance ML models tailored to specific PM tasks. Studies have shown that high-quality datasets are important for AI to work at its best. For instance, the Dynamic Project Duration Prediction (DPDP) tool, an ANN-based model, outperformed traditional forecasting methods using datasets from two IT firms (Lishner & Shtub, 2022). Lishner & Shtub (2022) found the model overall effective; however, its accuracy declined in smaller organizations due to limited data quality and availability.

3.10. Critical Issues in Implementing AI in Project Management Practices

While AI offers significant benefits in PM, its implementation faces key challenges that can hinder adoption and restrict the effective realization of its full potential (Shang et al. 2023; Vaghasiya et al. 2025). Applying the Technology, Organization, and Environment (TOE) framework (Tornatzky & Fleischer, 1990) to the findings from SLR, the SLR presents the following critical issues in implementing AI in PM practices.

First, regarding *technological factors*, one of these is the availability and reliability of datasets. The effectiveness of ML-driven PM tools depends heavily on data quality, accuracy, and consistency (Adamantiadou & Tsironis, 2025; Das et al., 2025; Lishner & Shtub, 2022). Incomplete or outdated data can compromise performance, and as Waqar et al. (2023) pointed out, data trustworthiness is essential for reliable AI predictions and successful PM integration. Besides, complex system integration and infrastructure demand also hinder AI adoptions in PM (Das et al.,

2025; Vaghasiya et al., 2025), which aligns with the TOE framework's emphasis on technology readiness (Tornatzky & Fleischer, 1990). Consequently, as noted by Hashfi & Raharjo (2023), these issues increase implementation costs and extend deployment timelines. Moreover, Sravanthi et al. (2023) also highlight limited access to essential technological infrastructure as a barrier to effective AI deployment in PM environments. Lastly on the technological factors, a technical skills gap has been identified as a major challenge in AI adoption for PM, especially in construction, where many professionals lack the expertise (Hashfi & Raharjo, 2023; Tian et al., 2025). In fact, the disruptive nature of AI technology demands continuous upskilling. Saxena & Totaro, (2024), therefore, stressed that PM roles now require data analysis, AI literacy, and collaboration with AI tools. Studies by Nyqvist et al. (2024) and Prasetyo et al. (2025) both emphasize training and skill development, including prompt engineering, as essential for effective AI adoption and use. In addition,

Second, regarding *organizational factors*, internal resistance issues, due to uncertainty, fear of job loss, and reluctance to embrace new technologies, also reflect organizational readiness challenges under the TOE framework (Alam et al., 2025; Alshaikhi & Khayyat, 2021). In this regard, Bandara & Wickramaraawan (2025) emphasized the need to balance automation with human judgment. Trust issues, often linked to limited understanding of AI systems and concerns about the reliability of AI solutions, exacerbate this resistance ((Barcaui & Monat, 2023; Fridgeirsson et al. 2021)).

Third, regarding *organizational factors*, ethical concerns and regulatory compliance present external challenges to AI adoption in PM. Alevizos et al. (2024) call for aligning AI innovations with ethical responsibility, while Waqar et al. (2023) stress addressing bias and fairness in sensitive areas like health and safety. Mohammad & Chirchir (2024) highlight gaps between ethical guidelines and real-world practice, urging structured ethical frameworks. Shang et al. (2023)

emphasize data privacy and security, advocating robust governance frameworks to maintain stakeholder trust in PM environments. These environmental considerations, including market trends and regulatory policies, underscore the TOE framework's role in shaping adoption outcomes.

3.11. Summary of Findings from SLR

The SLR yielded significant insights, highlighting a growing scholarly interest in the application of AI within PM, particularly in the domains of construction, IT, and software development. This body of research is predominantly concentrated in advanced geographical regions such as Asia and Europe, with comparatively limited attention directed toward underdeveloped regions, including Africa.

The literature reveals that while numerous AI tools have been integrated into PM functions, their effectiveness varies across different areas of application, which corresponds to the theoretical perspective of Taks-Technology Fit (TTF) model (Goodhue and Thompson, 1995). LLMs, especially GenAI such as ChatGPT, chatbots, and Copilot, have demonstrated particular strength in repetitive PM activities, text-based, offering automation capabilities that enhance efficiency and contribute to improved project delivery. In contrast, ML models, including fuzzy logic, SVM, and random forest, as well as DL, such as ANNs, have shown superior performance in tasks that are cognitive in nature. These techniques have proven effective in prediction and estimation functions, such as scheduling, cost management, risk assessment, and resource allocation. Despite these positive contributions, the literature also identifies technological, organizational, and environmental challenges associated with the integration of AI into PM practices, which corresponds to the Technology, Organization, and Environment (TOE) framework (Tornatzky &

Fleischer, 1990). Key issues include gaps in technical skills, internal resistance, technical limitations, data availability and reliability, and ethical concerns, among others.

Following the insights from the SLR, the following chapter presents the key informant interviews, which provide complementary industry perspectives on the integration of AI in project management.

CHAPTER 4: KEY INFORMANT INTERVIEWS (KII)

This phase of the study aims to complement the findings derived from the SLR on the impact of AI on PM practices by incorporating empirical insights obtained through interviews with industry experts based in Ghana. To achieve this, the research employed a qualitative approach through key informant interviews (KII) aimed at eliciting detailed information regarding the application of AI-driven tools and techniques in PM practices.

4.1 Qualitative Study Methodology

The current study employed semi-structured interviews with key informants, employing open-ended questions to elicit detailed responses (Creswell & Clark, 2018). A semi-structured interview allows the researcher to obtain in-depth responses and pursue follow-up questions for further clarification from the interviewees (Kite & Whitley, 2018; Kumar et al. 2022). The interviews with key informants were conducted via Microsoft Teams.

4.2 Selection of the Key Informants

Regarding the sample size for the qualitative interviews, existing literature provides guidance on the approximate number of interviewees necessary to achieve data saturation, which is the point at which no new information or themes are observed in the data. For example, Galvin (2015) recommended a sample size ranging from 11 to 17 participants for qualitative interviews. Similarly, Hennink et al. (2017) suggested that meaningful thematic saturation is typically achieved with 16 to 24 interviews, although code saturation may occur after nine interviews. For reference, previous qualitative studies have utilized varying sample sizes based on their research objectives and data saturation points. Nevertheless, previous research has demonstrated that saturation can be achieved with sample sizes ranging from 5 to 15 interviewees (Alam et al., 2025; Bandara & Wickramaraawan, 2025; Kumar et al., 2022; Lee et al., 2024; Shang et al., 2023; Wan

et al., 2021). Following the precedent established in the aforementioned studies, this study employed 11 key informants.

Given the study's aim to obtain insights from industry experts through semi-structured interviews, participants primarily include project management professionals such as officers from project management offices (PMOs), program managers, project managers, project leaders, project engineers, and related roles, each possessing a minimum of 5 years of relevant experience. The participants were selected from industries such as telecommunications/IT, banking and finance, construction, energy (oil and gas), and energy and mining. Consistent with the approach adopted by Shang et al. (2023), this study utilized the professional networking platform to connect with the PMI Ghana Chapter. Given the use of convenience sampling, this was deemed appropriate due to its cost-effectiveness and its ability to facilitate rapid access to potential participants (Shang et al., 2023). Initially, sixteen project management professionals were contacted and expressed willingness to participate in the study. However, due to scheduling conflicts and other unforeseen constraints, only eleven informants were ultimately able to take part.

4.3 Data Collection Process and Interview Questions

In addition to the initial identification and selection of key informants, a subsequent screening process was conducted during the informed consent stage. This involved administering a two-step screening questionnaire designed to confirm participant eligibility before proceeding with the qualitative interviews. This process was administered through the Qualtrics digital platform. Participants who met the eligibility criteria and provided informed consent were subsequently invited to schedule interview sessions within a designated three-week period during October 2025.

Prior to the commencement of each interview, participants were taken through a structured briefing session. During this session, they were reminded to exercise discretion regarding any non-

disclosure agreements (NDAs) associated with their current or previous projects, particularly when referencing specific project details during the interview process. Interviews with key informants were conducted via the Microsoft Teams digital platform. As part of the informed consent process, participants were requested to provide permission for audio recording of the interview using Microsoft Teams' built-in audio and transcript functionalities. Each interview had an average duration of approximately 45 minutes. The interviews were conducted online via Microsoft Teams by the lead investigator, who is also the author of this study.

With respect to the interview questions, the study developed seven broad, open-ended questions aligned with the research questions. These questions were designed to elicit detailed insights from key informants, industry experts in PM with the aim of complementing and enriching the findings derived from the SLR. To ensure objectivity in responses and minimize potential bias, the author intentionally refrained from disclosing any results or findings from the SLR prior to or during the interviews. As is characteristic of semi-structured qualitative interviews, follow-up questions were posed based on the participants' initial responses to elicit further clarification, probe deeper into emerging themes, and ensure a comprehensive understanding of the issues discussed.

At the end of each interview session, participants were taken through a debriefing process. The purpose of this debriefing was to inform participants about the nature and objectives of the study in which they had taken part, consistent with ethical research practices as outlined by Kite & Whitley, (2018). Additionally, participants were informed of their right to request the withdrawal of any portion of their responses should they believe that content subject to an NDA was mistakenly disclosed during the interview.

4.4 Data Analysis Procedure

The qualitative method employed in this study combined thematic and narrative analysis, drawing partially from Braun and Clarke's reflexive thematic analysis framework (Byrne, 2022). However, rather than following the conventional approach of generating initial codes prior to theme development, this study adopted an unconventional strategy: themes were developed directly from the conceptual structure of the interview questions. A thematic table was created to organize the qualitative data. The interview transcripts were first cleaned and then manually coded by the lead author, using descriptive narratives extracted from the transcripts. These codes were subsequently categorized under the relevant themes, enabling structured analysis and interpretation.

4.5 Findings from the Key Informant Interviews

4.5.1 Demography of the Key Informants

Table 8 presents a summary of the responses from eleven key industry experts, with both their identities and affiliated organizations anonymized. Five key informants work in Telecommunications and IT organizations, serving in senior roles such as Chief Technical Officer (CTO), Director of Network Operations, Project Director, Head of the Project Management Office (PMO), and Program Manager. Two informants work in Banking and Finance institutions as a Digital Project Manager and a Project Manager. Another two are drawn from Construction firms, holding positions such as Program Manager and Regional Director. The remaining two key informants work in Energy (Oil and Gas) and Mining companies, serving as Head of Business and Projects, and Project Engineer. Additionally, the informants brought extensive professional experience to the study, with backgrounds in project management spanning 10 to 25 years. Their educational qualifications were: two held doctoral degrees, while the remaining participants possessed master's degrees.

Table 8. Summary of key informant interview (KII) results

Participant	Position/Industry	Motivation for adopting AI	AI & ML tools currently used for their PM	PM areas (Knowledge-areas, processes, performance domains)	Benefits of AI in PM	Top 3 Challenges	Addressing the challenges
P1	* Chief Technical Officer (CTO) *Telecommunications *17 years in PM	* Efficiency of project delivery * Cost savings * Speed to market influenced by competition	* Google Workspace (Gemini) * Wrike	* Communications * Stakeholder management (collaboration) * Planning * Procurement (inventory management)	* Efficiency and productivity * Cost savings * Enhances speed to deliver solutions to clients	* User acceptance * Restructure the organization and legacy systems * Initial investment cost of deployment	* Training * Advocacy and demonstrating the benefits * Business case and benefit realization to the board
P2	* Director, Network Operations *Telecommunications * 11 years in PM	* Efficiency * Enhanced performance, Higher KPIs * Cutting waste, cost reduction, and improved budget * Stay updated with emerging technologies	* IRIVER (Proprietary tool) * Integrated Service Delivery Platform (ISDP) * Integrated Supply Chain Platform (ISCP)	* Planning * Project execution, monitoring and control * Quality * Procurement management * Inventory and resource management	* Supports intelligence analytics * Enhanced efficiency * Cost savings * Improves project lifespan (project timelines)	* Initial cost of investment * Technical skills gap * User acceptance	* Gradual approach * Training * Sensitization and user awareness of the tools
P3	* Digital Project Manager * Banking and Finance *11 years in PM	* Speed to market * Quick decision making * Improve efficiency * Effective collaboration * Push from competitors	* Linear * Figma (wireframing tool) * Adobe XD * Agile DevOps (Azure DevOps) * Asana * Trello	* Requirement, scoping * Project initiation * Time/Scheduling * Resource management * Execution * Monitoring and control * Project closure	* Visibility of the entire project * Enhances collaboration * Ease of accessibility * Improves project reporting * Clearly define milestones and improves time management * Efficient use of resources	* Fear of accountability * Internal resistance * Lack of in-person engagement and human interactions	* Schedule in-person stand up meetings * Engage in more team building activities

Participant	Position/Industry	Motivation for adopting AI	AI & ML tools currently used for their PM	PM areas (Knowledge-areas, processes, performance domains)	Benefits of AI in PM	Top 3 Challenges	Addressing the challenges
P4	* Project Director *Telecommunications *11 years in PM	* Efficiency * Automate repetitive tasks * Building capacity and readiness for the future * Competitive advantage	* C Module * ChatPDF * ChatGPT	* Planning * Predicting cost estimation * Project closure	* Efficiency * Help develop insights into projects * Help in trend analysis of project performance * Fast track request for proposal to clients * Minimizing error in reporting	* Lack of top management interest * Initial cost of investment * Possible loss of highly trained professionals with specialized expertise in AI (attrition)	* To conscientize top management on the benefits of AI in project management * Trained personnel will be required to complete a fixed bonding period
P5	* Program Manager * Construction * 20 years in PM	* Enhanced project management * Driven by competition	* Copilot * Gemini	* Monitoring and control * Risk management	* Improve project planning * Enhance predictions * Risk assessment	* Lack of organization-wide AI adoption in project management * Technical skills gap	* Training and professional development * Progressively developing project knowledge base
P6	* Project Manager * Banking and finance * 10 years in PM	* Efficiency * Focus on the core mandate by automating repetitive task * Cost saving * Improved project timelines * Augment and reduce workload * Driven by intense industry competition	* ClickUp * Jira * Copilot	* Planning (scheduling) * Execution * Monitoring and control * Project closure * Stakeholder management * Risk management	* Enhanced efficiency, faster delivery * Ensure greater visibility of the project * Improves project reporting * Enhances collaboration	* Internal resistance * User acceptance * Cost of the tools/initial investment	* Top management oversight pushes personnel for using the tools * Individual support

Participant	Position/Industry	Motivation for adopting AI	AI & ML tools currently used for their PM	PM areas (Knowledge-areas, processes, performance domains)	Benefits of AI in PM	Top 3 Challenges	Addressing the challenges
P7	* Head/Project Mgt Office (PMO) * Telecommunications * 21 years in PM	* Enhanced decision-making process * Improve efficiency * Reduce waste * Driven by technology advancement for innovation * Cost savings * Speed to market driven by competition	* Copilot * ChatGPT * Meta * DeepSeek	* Project initiation * Risk management * Planning * Cost estimation * Quality management	* Business analysis and business case justification * Strengthens decision process * Managing risks * Real time project tracking	* Technical skills gap * Lack of top management buy in (not incorporated into the business strategy) * Acceptance at the individual level	* Motivation for training * Encouragement for acceptance/usage * Progressive adoption/integration * Case benefits justification to top management
P8	* Program Manager * Telecommunications * 11 years in PM	* Enhanced productivity * Reduced work stress, worn out, fatigue * Efficiency (use of time) * Driven by competition to deliver products faster	* Copilot * Planner * Facilitator (AI functionality in Microsoft team)	* Risk management * Stakeholder management * Planning (scope, time, cost, quality) * Monitoring and controlling (Tracking progress)	* Improve productivity (time savings) * Automating tasks * Predictive analytics: resource management and project duration * Better decision-making * Enhanced collaboration across team * Enhanced reporting and stakeholder visibility	* Internal resistance; fear of AI replacing jobs * Cost of purchasing license * Technical skills gap	* Training * Sharing experiences * Partnership with Microsoft to reduce the cost of license per use * Putting in access control address ethical considerations
P9	* Regional Director * Construction and Engineering * 25 years in PM	* Efficiency in project management * Automate routine and repetitive tasks * Effective risk management; proactive risk identification * Effective resource management	* Microsoft project * Monday.com	* Monitoring and controlling (performance tracking * Resource management * Risk management * Time/scheduling * Stakeholder management	* Accuracy of time estimation * Automating routine tasks * Improving efficiency * Enhances resource allocation	* Data quality and privacy * Technical challenges (legacy systems) * Technical skills gap	* Change management initiatives * Training on AI * Develop new project management skills

Participant	Position/Industry	Motivation for adopting AI	AI & ML tools currently used for their PM	PM areas (Knowledge-areas, processes, performance domains)	Benefits of AI in PM	Top 3 Challenges	Addressing the challenges
P10	* Head of Business and Project Management * Energy (Oil and Gas) * 18 years in PM	* Driven by technological advancement * Motivated by AI added value * Replacement of inefficiencies * Serves as assistant and augment work process * Quality of work improvement	* DeepSeek * ChatGPT * Sensei (Proprietary) * Gemini * Copilot	* Initiation * Planning (scope, schedule, cost) * Execution * Monitoring and controlling * Closure *Risk management	* Reduces turnaround time for project deliverables * Efficiency (reduces the number of people performing the same tasks) * Good companion * More refined output * Serves as learning aid (experience)	* Technical skills gap * Perception of AI replacing humans * Responsible use, acknowledging the use and being accountable	* General training on AI tools * Assurance to the team that AI is an assistant * Supporting and sharing knowledge and experience
P11	* Project Engineer * Energy and Mining * 11 years in PM	* Seamless and flawless project delivery * To gain competitive advantage * Increase in quality of work * Provides and empowers experience to project team	* ChatGPT * Gemini * Copilot	* Project initiation * Project planning * Project execution * Project closure * Quality management * Communication management	* Reduces workload, speed up processes (Efficiency) * Serves as a learning for concepts and experience in project delivery * Minimizing errors in pre-project proposal process * It promotes quality of work and builds trust from clients * Serves as cost cutting tool	* Technical skills gap (Prompt engineering) * Initial cost of investment * Internal resistance	* Training: learning and development * Use of internal expertise for development of AI tools * Advocate the benefits and advantages of using AI tools

4.5.2 Motivations for Adopting AI in Project Management

The adoption of technology is usually influenced by a range of factors that vary according to industry characteristics and the strategic orientation of individual organizations. This pattern is similarly reflected in the uptake of AI-driven tools within project management, where adoption decisions are motivated by sector-specific priorities, operational needs, and organizational strategy.

As illustrated in ***Figure 9***, nine of the interviewees (27%) identified efficiency as a primary motivation for adopting AI in PM activities. This finding aligns with the broader evidence from the SLR, which similarly highlights efficiency gains as a key driver for the integration of AI tools into PM practices. Indeed, the interview findings suggest that increased automation through the use of AI tools reduces the burden of routine project tasks, allowing project managers to redirect their efforts toward higher-value activities. This perspective is consistent with prior research, which indicates that AI-enabled automation alleviates workload pressures and enhances overall project efficiency (Alam et al., 2025; Dimcheva, 2024; Prasetyo et al., 2025; Sarwar & Rahman, 2024).

The findings indicate that the second most frequently cited motivation for adopting AI in PM is the pursuit of competitive advantage (24%). This factor was particularly emphasized in industries characterized by strong competition, where organizations perceive AI-enabled project environments as a means to accelerate delivery timelines and strengthen market positioning (Felicetti et al., 2024). Notably, four informants specifically identified speed to market (12%) as a key driver influencing their organization's decision to integrate AI into PM practices. In a practical instance, a Program Manager from the telecommunications sector noted that their organization

occasionally utilizes code generated by GenAI to expedite product development and accelerate speed-to-market.

Four informants also identified cost savings (12%) as a key motivation for integrating AI-driven tools into PM practices. Although the initial investment cost was widely acknowledged as a challenge, these informants emphasized that, over time, the total cost of ownership (TCO) decreases, resulting in overall cost savings for the organization. Also in the same bracket, emerging technology (12%) was also cited by four intervewees as their motivation for adopting AI in their project activities. In this instance, organizations and individuals try as much as possible to stay updated with advances in technology. While some organizations have not yet aligned their business strategies to integrate AI as a source of competitive advantage, individual PM professionals within these organizations have independently taken steps to upskill in AI technology. For instance, the Head of Business and Project Management in one of Ghana's Oil and Gas sector reported personally pursuing training to enhance his knowledge in applying AI to PM. This informant is of the view that "If you don't develop AI expertise, AI will replace you". Similar sentiments were shared by a Program Manager in the construction industry and a Project Director in the telecommunications sector, reflecting a growing trend of individual initiative toward AI competency despite lack of organizational alignment. These informants expressed a strong belief that, given the rapid advancement of AI within the broader business ecosystem, failing to upskill and enhance their competencies could increase the likelihood of being displaced by AI-driven capabilities.

In addition to the primary motivations identified, two informants (2%) cited improved quality and another two informants (2%) highlighted enhanced decision-making as key factors influencing their organization's adoption of AI in PM. For example, the Head of Business and Project

Management in the Oil and Gas sector indicated that AI has enhanced the quality of deliverables provided to clients, which serves as a core justification for its integration. This experience was affirmed by a Project Engineer in the telecommunications industry, who reported using ChatGPT as a quality assurance tool to produce high-standard project documentation. A Digital Project Manager in the banking and finance sector, as well as a Head of the PMO in the telecommunications industry, both indicated during the interviews that their motivation for adopting AI tools in PM is driven by the ability of these tools to fast-track decision-making processes.

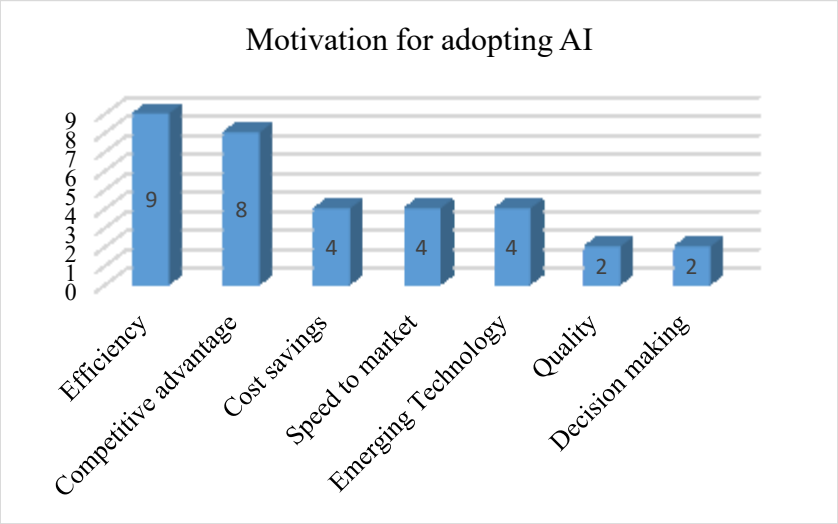

Figure 8. Motivation for adopting AI tools

4.5.3 AI Tools Currently being used in PM

The interview findings reveal a diverse range of AI-driven tools being used in PM. As shown in ***Figure 9***, ten (31%) tools were classified under "others," reflecting tools mentioned only once across the interviews. Examples of such tools include Wrike, Meta, Linear, Figma, Jira, ClickUp, Asana, Trello, Adobe XD, and Azure DevOps. Although less frequently mentioned, these tools

demonstrate the diversity of AI adoption and reflect the context-specific preferences of individual organizations and project teams. Moreover, GenAI tools (50%), including Copilot, ChatGPT, Gemini, and DeepSeek, collectively received the highest number of references from the interviewees. This observation aligns with the findings of the SLR, which identified GenAI as the most frequently applied category of AI tools in PM.

In contrast to the SLR, which found ChatGPT as the most widely used GenAI, the interview findings indicated that Copilot is the most frequently utilized AI tool, accounting for six references (19%). ChatGPT and Gemini followed closely, each cited four times (13%), while DeepSeek was referenced twice (6%). Surprisingly, none of the key informants mentioned Chabot, which has been reported in findings of the SLR as the second most used GenAI, alongside Copilot. More surprising is the fact that approximately 55% of informants came from service sectors like telecommunications, and, banking and finance where Chabot applications are widely applied. This may be explained by the perception of chatbots as routine or basic AI applications, with informants prioritizing more advanced solutions, or by their predominant use in customer-facing functions rather than PM tasks.

In addition to the above-mentioned AI tools, there are approximately six (19%) proprietary AI tools that were mentioned by the key informants. According to the informants, these tools were developed for specific PM functions. For instance, a Director of Network Operations in the telecommunications sector cited a proprietary tool called IRIVER, among others, used for project planning and other PM functions. According to this expert, although these tools are proprietary, they were introduced and shared by a key contractor to support the management of turn-key projects. Another informant, a Head of Business and Project Management at a large multinational oil and gas company, mentioned a proprietary tool called Sensei, being used by their project team

as well by the entire organization. Regrettably, the interviewees were unable to specify which specific ML models or algorithms were employed by these tools.

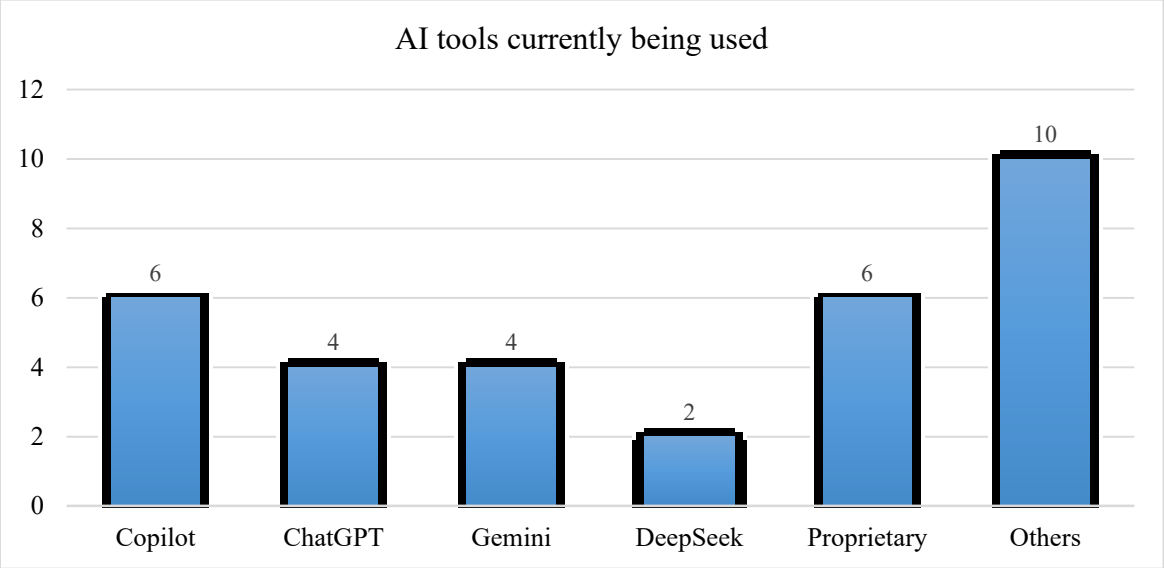

Figure 9. AI tools currently being used in PM

4.5.4 Project Management Areas Supported by AI Tools Used

First, based on the AI tools that key informants confirmed they are using to deliver their projects, ***Table 9*** displays the summary findings of the most frequently used PM tasks with these AI technologies. The findings indicate project planning (15%) as the most frequently project activity that AI is being applied to. This is followed by monitoring and controlling (12%) before risk management (10%). While monitoring and controlling were not present in the SLR, risk management, previously identified as the most researched PM activity, unexpectedly fell to the third most frequently used activity when utilizing the AI tool for project delivery. This may be attributed to the relatively small number of industry experts from the construction sector, where the SLR had noted risk management as particularly prevalent.

Second, both project execution and project closure were each mentioned five times (8%) by key informants as activities supported by AI tools. Surprisingly, project closure was absent from the SLR, yet emerged strongly in the interviews. This highlights the growing importance of AI in facilitating documentation and capturing lessons learnt within these organizations. Interestingly, project time/scheduling and cost were cited five (8%) and four times (7%), respectively. This is in contrast to the SLR, which identified these two activities as the second and third most researched areas in PM.

Third, both resource management and stakeholder management were each cited four times (7%) by key informants. Whereas, stakeholder management did not appear in the SLR, yet the interviews revealed moderate use of AI in this area. Informants recorded tools such as Copilot, which support collaboration among project teams and key stakeholders. Moreover, resource management appeared more in research in the SLR reviewed than was mentioned in the informant interviews. In a projectized environment, procurement management is closely linked to resource and inventory management. Therefore, the relatively low number of resource management activities reported by key informants is not unexpected. This difference may be explained by the two references to procurement activities (3%), which suggest that some resource-related functions were captured under procurement in the interviews.

Fourth, even though the SLR revealed no research focused on quality, three key informants, representing approximately 5%, noted the role of AI tools in improving project quality. Quality was identified as one of the PM activities that provides a competitive edge for their organizations. In this regard, a Project Engineer in the energy and mining sector emphasized how AI has been instrumental in delivering high-quality project outcomes for their clients. He further noted that this

consistent quality has helped build and sustain trust with their clients. Meanwhile, two interviewees mentioned communication, representing 3% of the PM activities using AI, which is consistent with the findings of the SLR. According to the informants, while these AI tools facilitate communications, they also help improve stakeholder engagement activities by streamlining interactions and improving information flow across project teams.

Table 9. Project Management Areas Supported by AI Tools Used

PM Areas	**Frequency**
Planning	9
Monitoring and controlling	7
Risk management	6
Execution	5
Closure	5
Scheduling	5
Initiation	4
Resource management	4
Cost estimation	4
Stakeholder management	4
Quality management	3
Procurement	2
Communications	2

4.5.5 Benefits from AI Tools for Project Management

First, the interviewees shared a range of benefits they derived from employing AI tools in PM. As summarized in ***Table 10,*** efficiency emerged as the most frequently reported benefit, cited by seven key informants and representing approximately 18% of responses. In fact, this aligns with the findings of the SLR, which identified efficiency as a key benefit of using AI, especially in

automating repetitive project tasks and streamlining routine processes. (Felicetti et al., 2024; Georgiev et al., 2024; Tian et al., 2025). Moreover, the strong emphasis on efficiency lends support to the positive role of AI in streamlining processes and reducing manual interventions, resulting in the overall performance of their project delivery. Consequently, the project delivery performance affirms the TTF framework, indicating that when technology (AI tools), task (PM tasks), and utilization are aligned, AI tools enhance project outcomes.

Closely following efficiency, the second most cited benefit of AI-driven tools in PM is speed of delivery, mentioned by six informants and representing approximately 15% of responses. Notably, those who emphasized this benefit predominantly work in highly competitive industries such as telecommunications and banking and finance. According to these informants, application of AI tools helps in accelerating product development cycles, thereby enabling faster time-to-market and helping their organizations maintain a competitive edge.

Second, five key informants identified prediction and tracking as key benefits of using AI tools, accounting for approximately 12%, while four informants considered enhanced project reporting as a benefit, representing 10%. The interviewees emphasized the importance of accurate data, noting that GenAI tools leverage historical information to improve predictive accuracy and ensure reliable tracking. They also reported that the shift from traditional manual reporting to automated processes, with AI-driven solutions provide real-time access to project reports for key stakeholders, including project sponsors.

Third, three key informants each identified cost savings, enhanced resource allocation, and enhanced collaboration as notable benefits of using AI in PM, with each benefit accounting for approximately 8% of responses. Although four informants mentioned cost savings as their primary motivation for integrating AI tools into PM, the number of responses identifying cost savings as

benefit was slightly lower. The difference in cost savings as a motivation for AI adoption compared to its benefits may indicate that the actual realization of these cost savings varies across different stages of AI adoption level within various organizations.

Fourth, two interviewees each cited automating routine tasks, improved productivity, strengthened decision-making, and accuracy of estimation as benefits of using AI in PM, with each benefit accounting for approximately 5% of responses. Even though the benefits laid out by the key informants appear distinct, they are linked together. For instance, automating routine tasks will eventually lead to increased efficiency and productivity in PM. Similarly, the SLR shows that AI-driven tools rely on accurate historical data to improve estimation accuracy, which in turn supports more informed and better decision-making.

Fifth, one informant expanded the discussion of AI's impact on PM to include negative effects in some instances. In this case, a Program Manager from a telecommunications industry noted that "overreliance on AI can produce shallow planning and stressed that human oversight". Consequently, contextual awareness remains critical when employing AI solutions in PM. The informants also identified data privacy concerns as a negative effect of AI adoption in PM, a view also shared by other interviewees. Moreover, this view aligned with the argument by Shang et al. (2023) on how the issue of ethical considerations is closely linked with data privacy and the need to protect sensitive data.

Table 10. Benefits of applying AI in project management

Benefits of AI in PM	**Frequency**
Efficiency	7
Speed of delivery	6
Predictions and tracking	5
Enhances project reporting	4
Cost savings	3

Benefits of AI in PM	Frequency
Enhances resource allocation	3
Enhances collaboration	3
Automating routine tasks	2
Improves productivity	2
Strengthening Decision making	2
Accuracy of estimation	2

4.5.6 Challenges Integrating AI Tools in Project Management

Integrating AI-driven tools, like any new technology, may face certain challenges that will hinder the adoption and slow down the rate of adoption in the organization following the TOE framework. Accordingly, the challenges are classified as technological, organizational, and environmental. The key informants were asked about the top three challenges they face when integrating or planning to integrate AI in their PM functions within their organizations. In fact, their responses confirm similar findings from the SLR on the critical issues in implementing AI in PM, which correspond to the Technology, Organization, and Environment (TOE) framework (Tornatzky & Fleischer, 1990) (See Table 11).

First, the technical skills gap (technical) becomes the topmost challenge in adopting AI in PM as seven informants cited it as their key challenge, representing approximately 26%. This aligns with Hashfi & Raharjo (2023) who found the existence technical skills gap required to deploy and effectively manage AI-based solutions in PM.

Second, while some key informants saw that using AI-driven tools in PM could save cost, six of them, making up about 22%, mentioned that they struggled with the high initial cost of investing in AI technology. This is consistent with the SLR, especially that of Hashfi & Raharjo, (2023),

indicating that the high cost of initial investment is the result of technical complexities in integrating AI into the existing PM systems.

Third, five interviewees identified low user acceptance, while four cited internal resistance as key challenges to adopting AI in PM, representing approximately 19% and 15% of responses, respectively. A project manager in the banking and finance sector attributed low user acceptance to the difficulty of using the new AI solutions, while a CTO in the telecommunications industry explained that "some team members were resistant because they had been accustomed to a particular tool for a long time." Their views are consistent with Fridgeirsson et al. (2021), who argued that PM practitioners are more willing to adopt AI when they trust it and have a clear understanding of how it works.

Fourth, three interviewees cited a lack of top management interest in integrating AI in their PM functions, representing approximately 11%. Without top management support for advancing AI in PM, organizations will struggle to align AI initiatives with corporate strategy and are unlikely to commit the necessary funding. A key informant from the telecommunication industry and the Head of PMO recounted how they struggled from the outset to secure top management buy-in. The informant explained that "top management is more likely to support AI initiatives for PM when presented with the benefits they offer to the organization."

Fifth, the availability and reliability of datasets, and technical challenges were identified as important barriers for AI adoption in PM in the SLR. Surprisingly, only one informant (approximately 4%) mentioned these issues as barriers in their organization. In order to realize accurate prediction and data that support decision-making, reliable and accurate data are critical. This is also consistent with Vaghasiya et al. (2025), who emphasized accurate, consistent, and comprehensive data to generate reliable predictions.

Concerning the issue of technical challenges, especially system integration, Vaghasiya et al. (2025) note that systems integration challenges arise from technical changes, driven by the complexity of modifying an organization's existing information systems infrastructure.

Table 11. Challenges of integrating AI in project management

Top 3 Challenges	**Frequency**	**TOE**
Technical skills gap	7	Technical
Initial cost of investment	6	Organizational
User acceptance	5	Organizational
Internal resistance	4	Organizational
Lack of top management interest	3	Organizational
The availability and reliability of datasets	1	Technical
Technical challenges	1	Technical

4.5.7 Strategies for Mitigating AI Implementation Challenges in Project Management

All eleven key informants shared various strategies they have used or are currently using to address the challenges encountered in integrating AI into PM activities. First, training emerged as a prominent solution. Given that AI is considered a disruptive technology (Shang et al., 2023), PM practitioners need to have continuous training to stay aligned with the rapid evolution of AI-driven solutions. While acknowledging the importance of training in AI for project managers, interviewees also emphasized the value of self-motivated learning to keep pace with evolving AI solutions. For instance, a Head of Business and Project Management in an oil and gas company resorted to self-directed training to avoid falling behind technologically. Similar sentiments were shared by a Project Director in the telecommunications sector and a Program Manager in the construction industry, both of whom stressed the need for continuous learning to stay relevant in

an AI-driven project environment. The PMI also acknowledges the importance of training for PM professionals by incorporating AI-related content into their PM training programs. For instance, a Digital Project Manager in the banking and finance sector referenced the use of PMI Infinity™, an AI-powered coaching tool recently introduced to support PM professionals in enhancing their skills and navigating the evolving landscape of AI in PM.

Second, regarding user acceptance and internal resistance, the key informants noted that they employed advocacy and benefit-sharing strategies to promote AI adoption in their project office. They also stated that they used change management initiatives and facilitated internal knowledge-sharing sessions, during which experienced PM professionals shared their firsthand experiences and the benefits of AI application to the broader project team.

Third, the key informants also described various strategies their organizations adopted to manage the initial cost of investing in AI integration for PM. One informant, a Program Manager at a Telecommunications Company, disclosed that their organization addressed this challenge by entering into a partnership with Microsoft Inc. to integrate Copilot across multiple PM systems. The informant noted that this partnership approach helped offset upfront costs while accelerating AI usage. Another participant, also from a telecommunications industry, revealed that their organization adopted a progressive approach integrating AI into PM. With this approach, the organization procures licenses for critical PM tasks only as needed, enabling cost-effective, targeted AI integration. Similarly, another interviewee, a Project Director from telecommunications industry, shared that their organization is considering adopting a gradual approach to integrating AI into their PM activities aimed at minimizing the initial cost of the solutions.

4.5.8 Key Informants General experience & insights from using AI in the PM

The key informants shared their general experiences and insights regarding the use of AI-driven tools in PM. They viewed AI integration positively, emphasizing its significant role in enhancing efficiency throughout the end-to-end delivery of their projects. With the rapid advancement and growing sophistication of AI solutions, the informants view AI as the future of successful PM. This perspective is reinforced by PMI's introduction of PMI Infinity™, an AI-powered solution designed to support project managers in effectively managing their projects. Notwithstanding its recognized benefits, AI adoption remains relatively moderate across various industries in Ghana. To address this gap, informants proposed the need for intensified efforts to encourage broader and widespread implementation. According to one informant, a CTO in the telecommunications sector, the newly launched national AI strategy in Ghana is expected to play a critical role in promoting and accelerating AI adoption.

One informant, a Regional Director from the construction industry, stated that "I believed that individual cultural backgrounds were influencing the adoption of AI in project management within our organization." This informant noted that these barriers may contribute to limited support from top-level decision makers, thereby impeding organizational buy-in. This cultural barrier appears to fuel a growing negative perception of the use of AI related solution. Supporting this view, a Head of Business and Project Management from the oil and gas sector confirmed that within their organization, individuals who rely on AI tools are sometimes perceived as lacking cognitive skills, further complicating efforts to promote AI use.

While acknowledging the positive impact of AI in PM, informants also voiced concerns about overreliance on AI for critical decision-making and execution. They stressed the importance of maintaining a balanced approach, advocating for the integration of AI as a supportive tool rather

than a replacement for human expertise. Besides this, the informants stressed the importance of responsible AI use, particularly in protecting the security of both data inputs and outputs. Moreover, the informants noted that ethical considerations have become a central concern in the development and deployment of AI technologies. These concerns have likely contributed to the recommendation that users employ GenAI with caution, carefully reviewing and validating AI-generated outputs before using them, especially in contexts involving critical decision-making. Indeed, a Program Manager from the telecommunications industry pointed out that AI developers may embed personal biases into AI tools. Highlighting the implications of such biases, a CTO from the same sector recounted a case in which a project engineer in their firm relied on an LLM to develop a technical solution for a client. Unfortunately, the output was suboptimal, resulting in the loss of valuable business opportunities. The informant warned that misuse of AI tools or reliance on inaccurate outputs can lead to serious repercussions, including reputational damage and, in some cases, legal consequences.

4.6 Integration of Findings from SLR and KII and Propositions for Future Research

The joint display of PM areas in *Figure 11* reveals both convergence and divergence between the Structural Literature Review (SLR) and Key Informant Interviews (KII). Both consistently emphasize risk management, cost, scheduling, planning, resource management, communications, and execution. Notably, planning and execution receive substantially greater emphasis in the KII data than in the SLR, indicating that practitioners prioritize the application of AI to these phases to a greater extent than is reflected in the literature. Conversely, the divergence between sources highlights differing research interests and practitioner priorities: the SLR places more emphasis on project outcomes and team-related issues, whereas the KII data stresses AI use in monitoring and controlling, project closure, initiation, stakeholder management, quality, and procurement.

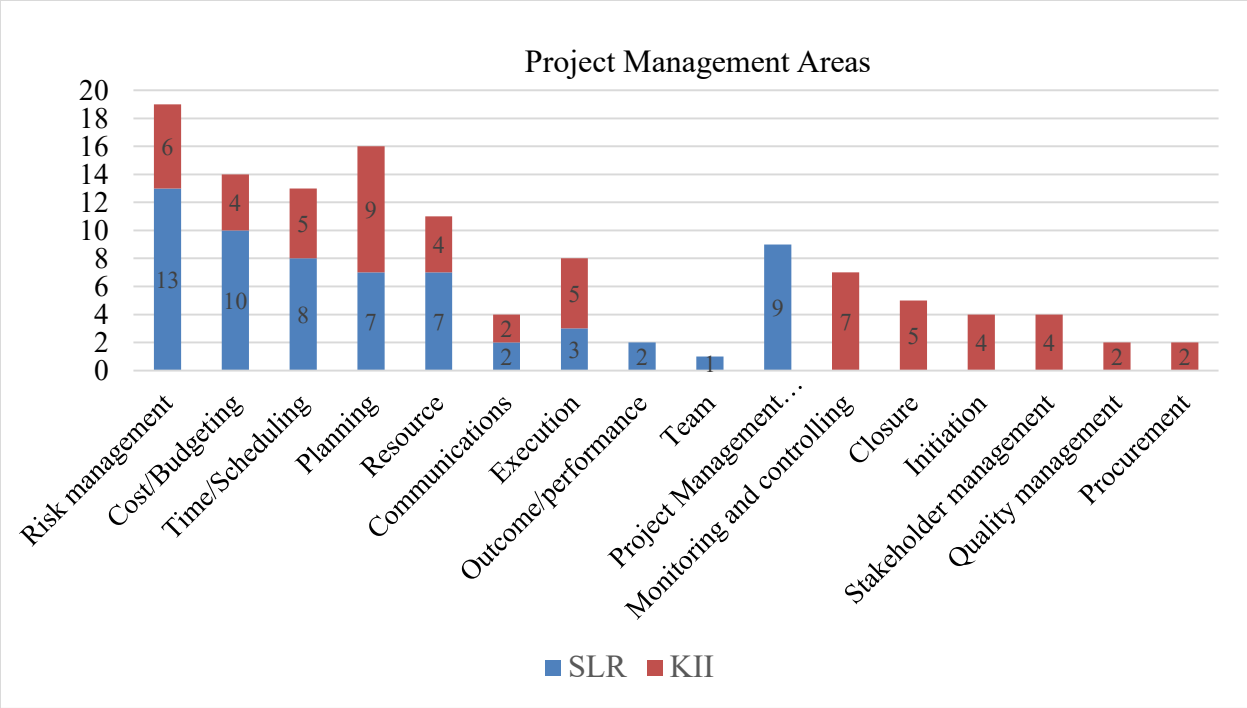

Figure 10 Joint display: PM areas from the SLR and KII

4.6.1. Propositions Regarding Motivations for Adopting AI in PM

The study demonstrates that both the SLR and the key informant interviews affirm that the primary motivations for adopting AI in PM are rooted in the benefits it provides, including enhanced delivery efficiency, competitive advantage, cost savings, and accelerated time to market, among others (Figure 8). This study observes that organizations motivated by the pursuit of competitive advantage are often influenced by the intensity of competitive rivalry within their respective industries, such as the service sector. The SLR identified competitive rivalry mostly in the software and construction industries, while similar dynamics were noted in the telecommunications and finance sectors in the interview results. However, competitive rivalry appears to be limited within the construction industry in Ghana. This phenomenon may be attributed to the structural

characteristics of the construction industry in Ghana. Building on this observation, future research could address this gap by examining variables related to industry dynamics (type, size, etc.) and their influence on the integration of AI solutions in project management. Methodological approaches such as cluster sampling may be employed to capture sectoral variations more comprehensively.

Proposition 1: Industry dynamics, such as industry type, degree of competitive rivalry, and firm size, significantly influence the extent to which AI solutions are integrated into project management practices.

4.6.2. Propositions Regarding the Benefits from AI

The SLR revealed that integrating AI solutions into PM activities enhances delivery efficiency (Alevizos et al., 2024; Das et al., 2025; Saxena & Totaro, 2024; Siddiqa et al., 2024). This aligns with the data from the key informant interviews, which identified efficiency as the foremost benefit of AI-driven solutions in PM. Closely associated with efficiency is delivery speed, identified in the SLR as a key benefit of AI in PM (Saxena & Totaro, 2024; Uddin et al., 2022; Vaghasiya et al., 2025) and also consistent with the key informant interview data. The study demonstrates that LLMs, particularly GenAI, predominantly support PM functions centered on text-based artifacts such as documentation, reporting, planning, and communication. In contrast, traditional ML models are primarily employed for cost and schedule estimation and predictive tasks, leveraging historical project dataset. This reveals a division in the functional capabilities of AI technologies within PM, with GenAI primarily supporting text-based tasks and ML models facilitating predictive estimations. Following this, the study proposes an integrated framework that leverages the complementary strengths of both GenAI's capacity for processing textual information and the predictive accuracy of ML. This hybrid model presents a possible avenue for future research.

Consistent with the findings of the SLR, key informant interviews also identified prediction and estimation accuracy as significant benefits of employing AI tools in project management. While the SLR results emphasized the role of ML models such as ANN, fuzzy logic, XGBoost (Elmousalami, 2021; Hazil et al., 2020), SVM, RF, and GBT (Maher & Alneamy, 2022; Sarwar & Rahman, 2024; Shamim et al., 2025) in achieving these outcomes, interview participants reported similar benefits through the use of GenAI. This divergence reflects an important shift in practice, suggesting that GenAI may extend or even redefine traditional approaches to predictive modelling in PM. Given this, future research should therefore investigate the comparative effectiveness of GenAI and conventional ML techniques, exploring not only their predictive capabilities and estimation accuracy (Cost, schedule, and risks), but also their integration within organizational workflows, and implications for decision-making in dynamic project environments.

Proposition 2: Integration of AI solutions in PM enhances delivery efficiency and speed, with GenAI primarily supporting text-based PM functions and ML models facilitating predictive tasks such as cost and schedule estimation.

4.6.3. Propositions Regarding the Challenges of Integrating AI Tools in PM

The study reveals that several challenges identified in the SLR, such as technical skill gaps, internal resistance, costs, and issues related to dataset availability and reliability, were also reported by key informant interviews. Applying the TOE framework, challenges were more in organizational factors than in technical factors, with some informants mentioning environmental considerations, notably ethical and governance issues. The study also highlights some practical shifts, like challenges associated with AI implementation in PM. While both the SLR and key informant interviews identified issues of dataset availability, reliability, and technical challenges, their accounts differ in the attribution of costs. The SLR emphasized infrastructure development as a

primary source of technical challenge and cost, whereas key informants linked the initial cost of investments mainly to procuring AI software solutions and licenses. This distinction explains the relatively low reporting of technical challenges in practice.

The study reveals a divergence between literature and practice regarding dataset availability and reliability as a challenge in AI adoption for project management. While the SLR emphasized the critical role of accurate historical datasets in developing ML models for predictions related to risks, costs, and schedules, industry experts reported such concerns at a much lower level. This difference can be explained by the reliance of LLMs, particularly generative AI, on pre-trained data rather than project-specific historical datasets used in ML models.

Taken together, future research can examine how different challenging factors negatively affect various aspects of AI implementation in project management. For instance, technical skill gaps, organizational resistance, and infrastructure costs represent universal barriers to AI adoption in PM. In contrast, issues of dataset availability and reliability are more closely associated with predictive AI (i.e., ML-based applications), whereas concerns about over-reliance on AI, as well as ethical and trust considerations, are particularly salient in the context of generative AI adoption.

Proposition 3: The impact of adoption barriers on AI implementation in project management varies by AI type, with technical skill gaps, organizational resistance, and infrastructure costs acting as universal challenges, while dataset reliability primarily constrains predictive AI applications, and ethical or trust concerns predominantly hinder generative AI adoption.

4.6.4. Propositions Regarding the Strategies for Mitigating AI Implementation Challenges in PM

First, both the SLR and key informant interviews emphasize technical training as a key strategy for addressing skill gaps in the integration and use of AI solutions in PM. However, the informants extend this recommendation by incorporating advocacy to promote broader utilization and acceptance of AI tools in PM (i.e. facilitation conditions). Leveraging internal teams to share practical experiences with AI solutions fosters organizational trust, enhances utilization, strengthens user acceptance, and reduces internal resistance. Nonetheless, the key informants did not address the potential effect of combining technical training with advocacy on the broader adoption of AI solutions in PM. To address this gap, the study proposes further investigation into the comparative effects of integrating these two approaches to evaluate their influence on the overall utilization and acceptance of AI in PM practices.

Second, the study identifies divergent approaches to addressing the cost of integrating AI technology into PM. While the SLR pointed out the expectation that long-term benefits will ultimately offset the initial investment costs, the key informant interviews emphasize more immediate, pragmatic strategies for managing upfront expenditures. These strategies include establishing partnerships with major service providers, adopting a phased approach to integration, and prioritizing targeted applications of AI solutions.

Third, the SLR highlights ethical considerations surrounding the integration of AI in PM, particularly with respect to data privacy and security. While challenges related to establishing an ethical governance framework were not strongly emphasized in practice, the key informants nonetheless point to the necessity of clear guidelines that can promote responsible development and broader application of AI in PM. Given this, future research should explore how

context-specific ethical frameworks for AI governance foster trust, safeguard data privacy, enhance security, and promote responsible use.

Proposition 4: Technical training, supportive organizational conditions, efficient cost management, trust in AI systems, and the implementation of context-specific ethical governance frameworks collectively mitigate challenges associated with AI adoption in project management.

4.6.5. Other Future Research Topics

Although interviewees endorsed broader adoption of AI in PM, they cautioned against excessive reliance and, consistent with the SLR, emphasized the necessity of balancing AI with human expertise. Accordingly, the study recommends future research on the role of human-AI collaboration in enhancing PM delivery.

CHAPTER 5: CONCLUSION: ACADEMIC CONTRIBUTIONS, PRACTICAL IMPLICATIONS, AND LIMITATIONS

The current study was conducted to review the impact of AI on project management practices and elicit the views and experiences of industry experts drawn from Ghana. The study provides both academic and practical insights, yet it faces certain limitations that suggest avenues for future research.

5.1 Academic Contributions

Research of this nature makes a valuable contribution to the expansion of academic knowledge. The findings from the SLR revealed compelling insights through the synthesis of existing studies in the field. There is a growing body of research focused on the application of AI in construction and IT/telecommunication projects from the SLR. Within these domains, AI is predominantly employed for risk management, cost, and scheduling. Furthermore, GenAI, particularly ChatGPT, Copilot, and Chatbot, emerged as the most widely applied AI-driven solutions across project management functions. The discourse becomes even more interesting when the key informant interviews reveal findings, some of which shifted from those of the SLR.

This study found archival data collection using SLR and surveys as the most commonly used research methodologies in the field. Although design science research is gradually gaining attention, its application has largely been limited to the development of ML models and algorithms tailored to specific AI solutions. Also, the field has seen limited use of qualitative research approaches, which underscores the uniqueness of this study in employing a mixed methodology that combines SLR with qualitative insights from key informant interviews. While the SLR did reveal a few instances of mixed-methods research, those studies typically integrated design science, experimental designs, and surveys, which are distinct from the qualitative emphasis

adopted in this study. Thus, this study has contributed to the enrichment of research methodologies in the field of AI used in PM by integrating SLR with qualitative inquiry.

Third, this study advances the theoretical understanding of AI adoption in project management by integrating insights from a Structural Literature Review (SLR) and key informant interviews to develop four future research propositions. By applying two theoretical perspectives from the Task-Technology Fit (TTF) and Technology Organization Environment (TOE) frameworks and also synthesizing evidence from both sources, the study bridges the gap between conceptual frameworks and practical realities, offering a multidimensional perspective on AI integration. Specifically, the propositions highlight (1) the influence of industry dynamics on AI adoption, (2) the functional differentiation and efficiency benefits of GenAI and traditional ML models, (3) the varying impact of adoption barriers across AI types, and (4) the mitigating role of organizational enablers such as technical training, cost management, trust, and ethical governance. This dual-method approach contributes to theory by extending the TTF and TOE frameworks into the AI-PM context, demonstrating how the fits between types of tasks (PMBOK areas) and technologies (AI types) and technological, organizational, and environmental factors interact to shape adoption outcomes. Furthermore, it provides a foundation for future empirical research to test these propositions, thereby enriching the discourse on AI-driven transformation in project management.

Finally, this study identifies gaps in the current literature in terms of geographical disparity. The SLR indicated a limited number of studies concentrated on underdeveloped regions, especially Africa, underscoring a geographic disparity in existing research. The incorporation of data from industry experts in Ghana renders this study particularly relevant and timely. Ghana is acknowledged for its progress in digital technology, especially in AI adoption, serving as a case study for the African region. Future research should, however, expand its geographical focus.

Expanding future studies to include other countries with similar levels of digital technology advancements will provide more comprehensive insights and improve the generalizability of findings.

Overall, this study provides an up-to-date synthesis of existing research, particularly highlighting developments from PMBOK7 and the latest AI tools and applications in PM. Beyond presenting a structured methodological approach and empirical findings on AI's impact, it also integrates detailed narratives from industry practitioners.

5.2 Practical Implications

Through the key informant interviews, this study revealed a range of benefits that organizations experience when applying AI solutions to their PM activities. Prominent among these are increased efficiency, speed of delivery, improved predictive capabilities and tracking, enhanced project reporting, and significant cost savings. These findings provide a strong foundation to motivate other organizations that are considering the integration of AI-driven solutions into their PM practices. Moreover, since PM is closely integrated with other strategic business units within an organization, the incorporation of AI-driven solutions can significantly enhance analytics and decision-making capabilities, resulting in achieving a broader corporate strategy.

This study has underscored the critical importance of high-quality data in the development of effective AI solutions (Adamantiadou & Tsironis, 2025; Das et al., 2025; Lishner & Shtub, 2022). Data accuracy is very important for the performance and accuracy of ML models, especially those that use historical datasets for predictive analytics and trend analysis (Hashfi & Raharjo, 2023). For instance, one of the key informants, a Regional Director in the construction sector, shared an account of how historical data was used to predict a potential risk in a road project. The AI tool had accurately identified a high-risk location; however, the warning was overlooked by the project

team. Unfortunately, the predicted risk later materialized. This shows the importance not only of data accuracy, but also of its availability and appropriateness within the project context. Without reliable and accurate data, the outputs of AI systems risk being flawed or misleading, which can compromise decision-making and project outcomes. A CTO in the telecommunications sector shared a case in which a project engineer once relied on an LLM to develop a technical solution for a client, but the results were suboptimal, ultimately causing the firm to lose the business opportunity.

This study highlights the strategic use of AI-driven tools in project management as a potential source of competitive advantage in Africa. The interviewees indicated that their organizations adopted AI solutions motivated by increased efficiency, expedited delivery timelines, cost savings, and competitive advantage. These tools facilitate the acceleration of product development cycles and improve responsiveness to changing market demands, thereby positioning organizations to surpass competitors (Saxena & Totaro, 2024; Shang et al., 2023; Tominc et al., 2023). Although competition was intense in service-oriented sectors such as telecommunications, banking, and finance in Ghana, the energy and mining industries also experienced moderate competitive pressure. Indeed, AI-driven solutions are reshaping competitive rivalry across firms within the industry. Even within public entities where inter-organizational competition is typically absent, the key informants revealed the presence of internal rivalry. As a result, departments and teams increasingly compete to adopt and leverage AI tools to enhance performance and streamline operations to outperform their counterparts.

For PM professionals, this study has demonstrated that the perception of AI replacing humans is largely unfounded. Both the SLR (Alshaikhi & Khayyat, 2021) and insights from key informant interviews dispel the fear that AI will fully displace human roles in PM. Instead, the findings

emphasize the importance of fostering a collaborative relationship between AI solutions and human expertise (Bandara & Wickramaraawan, 2025). Indeed, the key informants strongly advocated for the continuous development of AI competencies to keep pace with the rapid evolution of AI solutions in PM. They emphasized that it is not AI itself that replaces humans, but rather the lack of preparedness and adaptability among those who fail to upskill, especially in Ghana (or the African regions). In their view, organizations and individuals who do not invest in building AI-related capabilities risk being outpaced by the technology and losing relevance in increasingly data-driven project environments.

At the policy level, this research demonstrates the value of African countries establishing a robust AI governance framework to support ethical considerations, data privacy, and organizational trust. In fact, an AI policy framework provides guidelines for the development, use, and protection of sensitive data. The key informants explained that the existence of an AI policy framework will contribute immensely to the broader use of AI in PM.

5.3 Limitations

One of the key advantages of mixed-method research is its ability to balance methodological strengths and weaknesses, where the weaknesses of one approach are offset by the strengths of the other. However, it is important to acknowledge a few limitations encountered in this study. Firstly, the SLR may present limitations stemming from the inclusion and exclusion criteria applied. The evaluation of quality assurance benchmarks may have introduced intrinsic bias, thereby omitting studies that could have provided significant contributions to the research. Furthermore, the omission of professional and industry reports like Gartner, Statista, and similar sources may have limited the study's depth of findings.

Secondly, this study reviews the impact of AI on PM within underdeveloped regions of Africa. Ghana is known as one of the most advanced countries in Africa when it comes to technology and PM. However, simply looking at key informants solely from Ghana limits the study's geographical scope. This limited focus could limit how well the results apply to other African settings. In this context, future research should consider broadening the geographical reach to include other countries with comparable levels of digital technology to enrich the research findings.

Thirdly, the key informants shared insights based on their experiences with projects undertaken within their respective organizations. However, several of these projects were bound by NDAs and involved sensitive security considerations that required confidentiality. Consequently, some informants were unable to disclose specific details, which may have limited the depth and richness of the data collected.

Even though the PMBOK Guide transitioned from a process-based framework (PMBOK 6) to a value-based approach (PMBOK 7) in 2021, few studies in the SLR engaged with PMBOK 7. Indeed, the key informants continue to rely on PMBOK 6, indicating limited use of PMBOK 7. With the newly released PMBOK Guide: the Eighth Edition (PMBOK 8) in November 2025 (Project Management Institute, 2025), PMI has included AI-related project management practices, as well as adoption strategies. Given this, future research should explore PM approaches grounded in PMBOK 7 and PMBOK 8 to align more closely with emerging value-driven and AI-enabled practices.

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APPENDIX I: QUALITATIVE INTERVIEW QUESTIONS

1. Please tell me about your experience with artificial intelligence (AI) in general with project management.
2. Which AI or machine learning (ML) tools and techniques are currently being used in the management of projects in which you are involved? Please provide a detailed explanation.
3. Please describe the impact and benefits that the application of these AI tools and techniques has had on project management practices within your organization.
4. In which specific project management processes, knowledge areas, and performance domains are this AI and ML tools and techniques applied? Please provide a detailed explanation.
5. What are the primary motivations for adopting or integrating AI and ML into your project management activities? To what extent does competitive rivalry influence the adoption of AI/ML tools and techniques in your project management practices?
6. What are the top three challenges your organization encounters in adopting artificial intelligence tools and techniques within project management activities? How does your organization propose to address these challenges?
7. Are there any additional insights or observations you would like to share that may contribute to or support the objectives of this study?

APPENDIX II: DATA EXTRACTION TABLE FROM THE SLR

Go to:

https://drive.google.com/file/d/1hM4Ml9rDCNJ2VuS2NiqbQcLjr9GIz2Ta/view?usp=sharing

APPENDIX III: DECLARATION

I acknowledge the use of digital writing and research tools—Grammarly, QuillBot, Copilot, and ChatGPT—for paraphrasing and grammar support in this thesis, while affirming that all ideas, analyses, and interpretations are entirely my own.