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**Effect of Integrating Artificial Intelligence into Project
Management Office Tasks and Tools in Construction Sector -
Challenges and Opportunities**

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شكر وتقدير

الشكر لله أولاً وأخيراً على ما وهبنا من نعم ودفع عنا من نقم

أخص بالشكر والدي ووالدي على كل ما قدموه وبذلوه، أتقدم بالشكر أيضاً لعائلي الصغيرة زوجتي وأبنائي على كل الدعم، إخوتي وأصدقائي لكم مني كل الشكر والعرفان.

كما أتقدم بالشكر والعرفان لجامعة ميدأوشن على إتاحة الفرصة لدارسة مرحلة الماجستير والتي كانت بمثابة حلم يلوح في الأفق، الشكر لدكاترة المواد الذين شاركونا هذه الرحلة ولم يبخلوا علينا بالعلم والمعرفة والنصيحة.

أخص بالشكر أيضاً الدكاترة مشرفي البحث على حرصهم وسعة صدورهم وكأنهم يحملون على عاتقهم رفعة هذه الأمة.

أتقدم بالشكر والعرفان لجميع من ساندني ودعمني في هذه الأوقات الصعبة.

الباحث

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Abstract

The construction sector is increasingly exploring Artificial Intelligence (AI) to enhance project management efficiency and decision-making. This study investigates the integration of AI into Project Management Offices (PMOs) within the construction industry, focusing on environments characterized by complex project requirements, tight deadlines, and high stakeholder expectations. Using a quantitative research approach, data were collected through a structured survey targeting professionals in the sector. The survey assessed current PMO practices, the extent of AI adoption, perceived benefits, and challenges faced during implementation. Statistical analysis was conducted to evaluate five hypotheses, examining relationships between PMO functions, AI integration, and project performance outcomes. While results confirmed significant positive relationships between core PMO practices and project success metrics—such as cost, schedule, quality, and stakeholder satisfaction—the hypothesized moderating effect of organizational barriers on AI integration was not supported. This finding suggests the need for further research to refine measurement constructs and investigate other potential moderating variables. The study contributes to both theory and practice by providing empirical evidence on AI's potential to strengthen PMO capabilities in the construction sector and by offering recommendations for future research to deepen understanding of AI's transformative role.

Keywords: Artificial Intelligence, Project Management Office, Construction Sector, Project Outcomes, Organizational Barriers, Digital Transformation.

الملخص:

يستكشف قطاع البناء بشكل متزايد إمكانات توظيف تقنيات الذكاء الاصطناعي (AI) لتعزيز كفاءة إدارة المشاريع ودعم عملية اتخاذ القرار. تهدف هذه الدراسة إلى بحث دمج تقنيات الذكاء الاصطناعي ضمن مكاتب إدارة المشاريع (PMOs) في قطاع البناء، مع التركيز على البيئات التي تتميز بمتطلبات مشاريع معقدة، ومواعيد نهائية صارمة، وتوقعات عالية من أصحاب المصلحة. اعتمدت الدراسة على منهج بحث كمي، حيث جُمعت البيانات من خلال استبانة مهيكله استهدفت المتخصصين في القطاع. تناولت الاستبانة تقييم ممارسات مكاتب إدارة المشاريع الحالية، ومدى تبني الذكاء الاصطناعي، والفوائد المتصورة، والتحديات التي تواجه التنفيذ. وقد أُجري تحليل إحصائي لاختبار خمسة فروض بحثية، لدراسة العلاقات بين وظائف مكاتب إدارة المشاريع، ودمج الذكاء الاصطناعي، ونتائج أداء المشاريع. أظهرت النتائج وجود علاقات إيجابية ذات دلالة إحصائية بين الممارسات الجوهرية لمكاتب إدارة المشاريع ومؤشرات نجاح المشاريع، مثل التكلفة، والجدول الزمني، والجودة، ورضا أصحاب المصلحة. في المقابل، لم تدعم النتائج الفرضية المتعلقة بالدور المعدل للعوائق التنظيمية في دمج الذكاء الاصطناعي، مما يشير إلى الحاجة لمزيد من الأبحاث لتطوير أدوات القياس ودراسة متغيرات معدلة أخرى محتملة. تسهم هذه الدراسة في إثراء الجانب النظري والتطبيقي من خلال تقديم دليل تجريبي على قدرة الذكاء الاصطناعي في تعزيز كفاءة مكاتب إدارة المشاريع في قطاع البناء، وتقديم توصيات للباحثين المستقبليين لتعميق الفهم حول الدور التحويلي للذكاء الاصطناعي.

الكلمات المفتاحية: الذكاء الاصطناعي، مكتب إدارة المشاريع، قطاع البناء، نتائج المشاريع، العوائق التنظيمية، التحول الرقمي.

List of abbreviations:

Abbreviation	Full Form
ACCESS	Academic Collaborative for Computing Education in Software Systems
AEC	Architecture, Engineering, and Construction
AI	Artificial Intelligence
BIM	Building Information Modeling
CO	Construction Outcomes (<i>verify exact meaning in your context</i>)
DOI	Digital Object Identifier
EMEA	Europe, Middle East, and Africa
ENTRENOVA	ENTRENOVA Conference (Enterprise Research Innovation Conference)
IBM	International Business Machines Corporation
IEEE	Institute of Electrical and Electronics Engineers
IJACSA	International Journal of Advanced Computer Science and Applications
IJTIP	International Journal of Technology and Information Processing (<i>verify exact title</i>)
INVOTEK	Innovative Technologies (<i>verify meaning in context</i>)
IPMA	International Project Management Association
IT	Information Technology
ITS	Intelligent Transportation Systems (<i>verify meaning in context</i>)
MIS	Management Information Systems
ML	Machine Learning
NLP	Natural Language Processing
OLS	Ordinary Least Squares
PEOU	Perceived Ease of Use
PLOS	Public Library of Science
PLS	Partial Least Squares
PM	Project Management
PMBOK	Project Management Body of Knowledge
PMI	Project Management Institute
PMO	Project Management Office
PMP	Project Management Professional
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PU	Perceived Usefulness
RMP	Risk Management Plan (<i>verify meaning in context</i>)
ROI	Return on Investment
SE	Structural Equation (<i>verify meaning in context</i>)
SEM	Structural Equation Modeling
SENET	Smart Energy Network (<i>verify meaning in context</i>)
SPSS	Statistical Package for the Social Sciences
SSRN	Social Science Research Network
TAM	Technology Acceptance Model

Abbreviation	Full Form
TOE	Technology–Organization–Environment Framework
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor

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Chapter One: Introduction

1.0 Introduction:

In recent decades, project management has been going through significant transformation. Project management evolved from been informal and reactive practices to structured, well-established frameworks, methodologies, tools, and organizational frameworks (Shamim, 2024). Project Management Office (PMO), plays a crucial role in standardizing project practices, allocating resources, enforcing governance, to make sure that projects are align with organizational goals. Recently, PMOs become a strategic hubs that provide consistency, efficiency, and excellence during the project delivery (Vukadinović & Fabac, 2022).

As the Fourth Industrial Revolution continues to develop and also digital technologies, new technology has emerged rapidly, which includes Artificial Intelligence (AI). AI technologies started to offer the ability to process massive amounts of data, detect patterns, make predictions, automate repetitive tasks, and simulate complex human decision-making using machine learning (ML), natural language processing (NLP), computer vision (CV), big data analytics, internet of things (IoT), robotics, and expert systems. These technologies are already reshaping how businesses operate and deliver value (Rampini & Cecconi, 2022; Silitonga & Jin, 2024).

PMOs, during evolutions of it provided support for organizations on process discipline, standardization, and oversight within project management practices. The integration of AI within PMO daily functions and tools can presents a complex framework of opportunities and challenges. However, the incorporation of AI has the potential to fundamentally transform the execution of project activities, the decision-making methodology, and the generation of value within organizations. Academic exploration of the implications associated with AI integration is needed, particularly in terms of process innovation, decision-making enhancement, and overall organizational impact. The use of AI is not considered like technological upgrade, but a fundamental shift to how PMOs can contribute to project success and achieve business strategy (Ibadildin et al., 2025; Salimimoghdam et al., 2025).

This study highlights the significant potential of AI to improve Project Management Office (PMO) performance, but achieving effective implementation will requires further development. Organizations willing to adopt AI might face several critical questions: Which PMO tasks are most suitable for enhancement through AI? What technical, organizational, or cultural barriers might arise? How to manage can resistance to change effectively? What ethical considerations need to be addressed? How to measure the impact of AI be measured in proper ways?

The study will offer a comprehensive analysis for the integration of AI into Project Management Office PMO functions within the construction sector. It aims to identify key opportunities and challenges, bridge existing knowledge gaps, and provide practical insights that can support AI adoption by organizations to enhance their overall performance and achieve more strategic and impactful outcomes.

1.1 Study problem.

Since the rapid development of AI as a transformative force in different industries, there is still notable gap in adopting AI technologies into Project Management Office functions and understanding the impacts, both positive and negative. This challenge is especially important considering the investments organizations make in both PMO infrastructure and AI technologies, especially with the absence of a clear strategy to align these resources for optimal organizational strategic outcomes (Salimimoghadam et al., 2025).

This study will try to fill gaps in knowledge related to understand AI adoption. First, there is limited practical evidence on PMO tasks that are suitable for AI enhancement, as organizations face challenges in finding practical guidance for the implementation of AI. Second, some organizations struggle to understand the feasibility and value of AI technologies. Third, the technical, organizational, and ethical barriers to integrating AI within PMOs is not much studied, and there is a shortage in existing literature to address these challenges. Furthermore, structured frameworks for assessing return on investment (ROI) in this domain are currently lacking (Shamim, 2024).

Additionally, the required changes by organization for integrating AI is underestimated which include change of work culture, workflow, and leadership. Also, the absence of clear implementation frameworks or roadmaps leaves project professionals without adequate guidance for AI integration. Finally, the potential benefits of AI are generally acknowledged, but there is a notable lack of practical research that quantifies these advantages specifically within the context of PMOs (Salimimoghadam et al., 2025). Therefore, This study aims to address these deficiencies by systematically examining AI integration into PMO functions within the construction sector, identifying possible challenges and opportunities, and getting insights to facilitate informed strategic decision-making.(Adamantiadou & Tsironis, 2025)

1.2 Study Importance:

The importance of this study comes from its contributions to the academic sector by understanding how Artificial Intelligence can be integrated into Project Management Office functions within the construction sector. The existing literatures has examined AI applications in project management, but significant gap remains regarding its specific role in enhancing overall function PMO processes, governance, and strategic alignment in construction projects. The study extends current theoretical frameworks by exploring this gap to offer practical evidence that may inform future academic work. It also builds on recent systematic literature reviews and emerging research that highlight the transformative potential of AI in organizational project management. Also, research study contributes to the understanding of the benefits and challenges of AI implementation within the project management domain, which is still an under-researched area (Hashfi & Raharjo, 2023).

The study will focus on current literature and explore the practical effects of AI integration in PMO environments and highlights suitable tasks within the PMO that can benefit from AI enhancement. It also explores the challenges and opportunities that come with implementing these technologies therefore provides valuable insights for both researchers and PMO professionals in the construction field.

The results for doing this study will provide important insights for organizations, helping them make better decisions when it comes to investing artificial intelligence, especially in PMOs by improving operational efficiency and supporting strategic alignment in complex construction projects. These findings can lead to notable improvements in project results. Additionally, this study contributes to the broader conversation about digital transformation in project management, setting the stage for future discovery in this fast-evolving field.

1.3 Study Objectives:

The main objective of this study is to examine the integration of AI into the tasks and tools of PMOs, with focus on the opportunities and challenges introduced by this technological evolution by the following specific objectives:

1. **Assess the current landscape** of PMO functions and tools and identify specific areas where AI technologies could enhance performance, improve capabilities, or address existing limitations.
2. **Identify and classify the primary challenges** associated with AI integration in PMOs, including technical, organizational, ethical, and implementation-related issues.
3. **Explore the opportunities and added value** that AI can bring to PMO operations, particularly in terms of improving efficiency, effectiveness, and strategic contribution.
4. **Gather insights from existing literature** on AI implementation across project management environments in various industries, highlighting common trends, success factors, and recurring obstacles.
5. Develop a **practical framework** to support the successful integration of AI into PMO functions, covering both technical implementation and organizational change management aspects.
6. **Provide actionable recommendations** for PMO leaders and decision-makers on how to approach AI adoption strategically maximizing benefits while effectively managing associated risks.

Together, these objectives aim to produce a balanced understanding of AI's impact on PMOs, offering both theoretical insight and practical guidance to support real-world integration.

1.4 Research Questions

This study on “Effect of Integrating Artificial Intelligence into Project Management Office Tasks and Tools in Construction Sector - Challenges and Opportunities” seeks to answer the following study questions:

- Q1. What is the current status of PMO tasks and tools in the construction sector, and which of these are most suitable for development using AI technologies?
- Q2. What are the main technical, organizational, and cultural challenges to integrating AI technologies into PMOs?
- Q3. How can AI technologies enhance PMO efficiency and impact in the construction sector?
- Q4. What are the expected future trends for adopting AI technologies in PMOs within the construction sector?

These questions have been designed to closely align with the survey questionnaires developed for this study, thereby ensuring that the collection and analysis of data remain consistent with the study’s objectives.

1.5 Study Hypothesis

This study was designed to examine the relationship between the integration of Artificial Intelligence (AI) technologies and the performance of Project Management Offices (PMOs) in the construction sector. Accordingly, the following hypotheses have been formulated:

Hypothesis 1: There is a statistically significant relationship between the integration of AI technologies and improvements in PMO functional effectiveness in the construction sector

Hypothesis 2: Technical, organizational, and ethical challenges significantly influence the successful integration of AI into PMO operations in construction projects.

Hypothesis 3: The integration of AI technologies significantly enhances the strategic value delivered by PMOs in construction projects, particularly in governance, decision-making, and portfolio optimization.

Hypothesis 4: The adoption of AI tools in PMOs is positively correlated with increased efficiency in project governance, decision-making, and task automation.

Hypothesis 5: Organizational readiness and change management practices significantly moderate the relationship between AI integration and PMO performance in the construction industry.

These hypotheses aim to provide a structured approach to examining the multifaceted impact of AI on PMOs, covering aspects from functional effectiveness to strategic value and operational challenges.

1.6 The scientific theory used to prepare the research

This study is based in two theoretical models: the **Diffusion of Innovations Theory (DOI)** and the **Technology Acceptance Model (TAM)**. These theories can provide a robust foundation for understanding the mechanisms behind the adoption and integration of Artificial Intelligence (AI) within Project Management Offices (PMOs) in the construction sector (Blythe, 1999).

The **Diffusion of Innovations Theory**, which was developed by Everett Rogers, explains how new technologies spread across social systems over time. It highlights five critical factors that influence the integrating process of new technology: relative advantage, compatibility, complexity, trialability, and observability. AI integrating in PMOs can be seen as a process progressing through the stages of knowledge, persuasion, decision, implementation, and confirmation. The study by Aizstrauta et. al (2015) explored the DOI theory by how organizational factors, communication structures, and perceived characteristics of AI, can influence the rate and success of its diffusion within construction project environments (Aizstrauta et al., 2015).

The second model is **Technology Acceptance Model (TAM)** which adds an individual-level perspective. It focuses on how users' perceptions shape their intention to use AI tools. It centers on two key elements: **Perceived Usefulness (PU)** and **Perceived Ease of Use (PEOU)**, which when combined can determine user acceptance level (Aizstrauta et al., 2015; Na et al., 2022). This model helps explain how PMO team members and stakeholders can evaluate AI systems in terms of added value and usability, and the effect of their willingness to adapt and engage with this new technology.

By using both DOI and TAM, the research can comprehensively analyze AI integration into PMOs functions by considering both the macro-level organizational spread and micro-level individual acceptance. This combination of both models can provide an understanding of success factors and challenges in PMO contexts (Felicetti et al., 2024).

. This study combines two theoretical perspectives:

Independent Variable- AI Integration into Project Management Office Functions.

Dependent Variable- PMO Effectiveness and Strategic Value Contribution.

The third variable is the **moderating variables** - which impact the relationship between AI integration and PMO effectiveness including: Organizational readiness, Change management practices, Ethical and technical barriers. These moderating variables are considered because they can influence the strength and nature of how AI integration affects PMO effectiveness and strategic value.

This theoretical structure supports the empirical investigation and hypotheses and analysis tools to examine how AI affects project governance, decision-making, resource management, and overall project performance in construction PMOs. It can also allow for a good understanding of both the macro-level publishing of AI technologies across organizations and the micro-level acceptance by individual users. (Venkatesh, 2022)

Chapter Two: Previous Studies

2.0 Introduction

This chapter will present a comprehensive review of previous studies that was conducted about the integration of artificial intelligence within project management offices, especially the ones related to the construction industry. Also, will provide a historical overview and discussion of the development of PMOs AI technology, and outline the evolution of these two domains, underscoring significant milestones and technological advancements that have paved the way for their present-day convergence in optimizing project delivery (Tominc et al., 2024)

2.1 Project Management Offices (PMOs):

2.1.1 History and Evolution

The concept of a Project Management Office (PMO) has evolved over the past century as projects have grown in both scale and complexity. Its early roots can be traced to the rise of scientific management in the early 20th century—particularly the work of Frederick Taylor—who focused on systematic approaches to planning, coordination, and efficiency (Giraud & Monaldi, 2015). Then in the 1930s, one of the earliest documented “project offices” was established by the U.S. Air Corps to oversee aircraft development, marking a practical application of centralized project governance.

Later during the 1950s, the U.S. military advanced this concept by introducing “System Program Offices” (SPOs) to manage complex weapons programs composed of numerous interrelated sub-projects. As a result, early PMO structures showed the value of centralized oversight, including integrated planning, standardized procedures, and enhanced cost control. Next in the 1980s, the adoption of computing tools for project scheduling and tracking provided more support for the expansion of PMO practices beyond the defense sector into industries such as construction and information technology (Umasekar, 2024).

The 1990s witnessed a global proliferation of project management standards and professional organizations. Methodologies such as PRINCE2, originating in the UK, extended PMO practices to new sectors, while the Project Management Institute (PMI) in the USA and the International Project Management Association (IPMA) in Europe gained significant influence. This era reinforced the necessity for structured governance to address the growing number and complexity of projects, prevent cost overruns, reduce delays, and resolve resource conflicts.

During the 1990s, the development of project management standards and the emergence of professional organizations such as PMI and IPMA and methodologies such as PRINCE2, improved the adoption of PMO practices across many sectors. The Project Management Institute (PMI) in the United States and the International Project Management Association (IPMA) in Europe established their influence into PMOs. This period was critical because of the need for structured governance frameworks to cope with the increasing scale and complexity of projects to better mitigate cost overruns, minimize delays, and address resource allocation challenges (de Almeida, 2024)

By the 21st century, PMOs had evolved from administrative support units into strategic ones which help organizations to be aligned with business objectives. Currently, PMO become

embedded in different organizations worldwide such as IT, finance, construction, and other sectors. And PMO not only focus on standardizing processes and monitoring performance but also enabling strategic portfolio management and ensuring projects deliver the intended business value. Over time, the PMO has shifted from a monitoring role to a central driver of organizational excellence.(Giraudo & Monaldi, 2015; Silvius, 2021).

2.1.2 Definition and Roles

There is no single formula for a PMO – its form and function can vary considerably between organizations (“no one-size-fits-all”). In essence, however, a PMO is an organizational structure dedicated to centralizing and coordinating the management of projects. PMI’s *A Guide to the Project Management Body of Knowledge (PMBOK®)* defines a PMO as “*an organizational structure that standardizes the project-related governance processes and facilitates the sharing of resources, methodologies, tools and techniques*”.

As stated by the definition above, the PMO sets common standards and best practices for project execution, provides support services (such as training, templates, lessons learned), and often oversees governance to make sure projects align with organizational goals and objectives. Depending on its intended role, a PMO's responsibilities may range from advisory (providing consultative support to project teams) to directive (having authority to manage projects directly). For example, PMI categorizes PMOs as supportive, controlling, or directive based on the degree of control they have, and as project-specific, departmental, or enterprise-level based on their scope within the organization. Despite these variations, the role of any PMO is to enhance consistency and predictability in project delivery (Silvius, 2021)

A well-functioning PMO can help organizations with better project selection and prioritization, better efficient resource utilization, and improved project success rates by applying uniform standards and leveraging organizational knowledge. PMOs also taken the role on strategic level functions such as portfolio management, benefits realization, to bridge the gap between project execution and organizational strategy (Umasekar, 2024).

2.2 Artificial Intelligence (AI):

2.2.1 Historical Background

Artificial Intelligence (AI) as a formal field of study was born in the mid-20th century. The term “**Artificial Intelligence**” was found in **1956** at the Dartmouth College conference organized by computer scientist John McCarthy. During the conference researchers gathered to explore the possibility of creating machines that could simulate human intelligence, marking the official beginning of AI research. McCarthy and colleagues hypothesized that aspects of human intelligence (such as learning and reasoning) could be precisely defined that a machine could be built to simulate them. Early AI research resulted in the 1950s–1960s programs that could solve algebra problems, prove logical theorems, and play chess, which led to optimism about rapid progress of AI research (Haenlein & Kaplan, 2019).

However, the field also encountered periods of slower advancement (the so-called “AI winters” of the 1970s and late 1980s) when lofty early expectations failed to materialize. From the 1990s onward, AI entered a new growth phase due to improved computing power, larger data availability, and new algorithms. Notable milestones such as IBM’s **Deep Blue** defeating a chess champion in 1997 and the proliferation of machine learning techniques in

the 2000s demonstrated AI's growing capabilities. In the 2010s, **deep learning** (multi-layer neural networks) revolutionized fields like computer vision and speech recognition, propelling AI into mainstream applications (from virtual assistants to self-driving cars).

Today, AI development is truly global – driven by research and investments across North America, Europe, and Asia – and is recognized as a key facet of the Fourth Industrial Revolution worldwide. The global AI research community continues to push toward more general and autonomous forms of AI, while governments and industries invest in AI for its transformative potential in the economy. This historical trajectory shows AI's evolution from an academic curiosity in the 1950s to a pervasive technological force in the 2020s (Darko et al., 2020).

2.2.2 Definitions and Concepts

AI has been defined in various ways over time, reflecting its broad scope. A classic definition by **McCarthy et al.** describes AI as *“the science of making a machine behave in ways that would be called intelligent if a human behaved similarly”*. In a similar vein, AI pioneer **Marvin Minsky** defined it as the effort to make machines *“carry out tasks that would require intelligence if done by humans”* (Adebayo et al., 2025).

These definitions emphasize that AI systems can copy human behaviors associated with human intelligence such as learning, reasoning, problem-solving, perception, or language use. Modern definitions of AI often center on the idea of intelligent agents: systems that perceive their environment and take actions to maximize their chances of achieving goals (Russell & Norvig, 2022). In practice artificial intelligence is considered an umbrella term for computer systems or machines that can simulate cognitive functions such as understanding, learning from experience, adapting to new inputs, and performing tasks that usually require human intellect.

2.2.3 Key subfields of AI include:

Machine Learning (ML): ML is techniques that allow computers to learn from data and improve their performance over time without being explicitly programmed for every scenario. For instance, ML algorithm can be trained from historical project data to recognize patterns and make predictions. This is why ML is often defined as the ability of a computer to extract patterns from data and learn to make decisions/predictions based on those patterns. ML has different sub-categories such as, deep learning, which uses multi-layered neural networks to handle huge datasets and complex patterns, as a result of this combination it can enable advances in image and speech recognition (Dodge et al., 2019).

Natural Language Processing (NLP): Is a branch of AI that deals with understanding and generating human language by allows AI systems to interpret text or voice inputs. One common example of this type is chatbots, which can search project queries and provide answers (Neveditsin et al., 2025).

Computer Vision: another AI technique to interpret and understand visual information from the world by recognizing objects in images or video. In construction, computer vision can enable automated progress monitoring or safety inspections by analyzing site photos.

Expert Systems and Reasoning: These AI systems encode expert knowledge to make decisions or solve problems in specific domains. For example, an expert system can be used to provide guidance on project risk management by drawing on a knowledge base of best practices.

Robotics and Autonomous Agents: This is an example of the integration of AI in machines that can perform tasks in the physical world. This includes robots that use AI to navigate and perform construction tasks, or software “agents” that autonomously execute tasks in digital environments

AI is thus multifaceted, and its definition shows a range of computational techniques aiming to mimic intelligent behavior. This explains what makes a system "AI" is its ability to perceive, analyze, decide, and act in a way that appears intelligent or adaptive. Modern AI systems can process huge number of datasets, learn from feedback, and operate autonomy. For example, an AI application can not only learn from historical project data to forecast outcomes, but also adapt its recommendations as new data arrives, which shows a level of responsiveness and input far beyond traditional software (Shamim, 2024)

Nowadays AI is recognized as a general-purpose technology, with its development driven by international collaboration among academic institutions, industries, and governments. Its integration into initiatives like "Industry 4.0" and "Construction 4.0" highlights how AI has become worldwide, especially in the digital transformation of various sectors. In summary, the author sees AI as the pursuit of machine intelligence – creating systems that can perform tasks that typically needs human intelligence and benefit from techniques such as machine learning to robotics to help enable it intended capability.

2.3 AI in Project Management

2.3.1 Enhancing Decision-Making and Efficiency

The integration of AI into project management has rapidly become a significant area of researcher’s interest. Organizations in different sectors including construction nowadays recognize AI's potential to improve project outcomes. AI technologies can enhance project management by automating routine tasks, providing data-driven insights, discovering trends, risks, and assisting in complex decision-making. For example, AI systems can automatically collect and analyze project data (schedules, budgets, quality, risk logs, etc.), to helps project managers identify trends and issues much faster than manual methods.

A recent PMI market analysis highlights that the global market for AI in project management is projected to grow from about USD 2.5 billion in 2023 to USD 5.7 billion by 2028 (a 17.3% annual growth rate)(Sahadevan, 2023). This growth clearly reflects a broad, global drive to leverage AI for organizations and projects success. AI is revolutionizing project efficiency and predictability, organizations are leveraging AI tools to automate repetitive tasks, extract insights from data sets, support decisions, and serve as intelligent assistants that actively empower project managers and teams.

2.3.2 Intelligent Scheduling and Resource Allocation

AI can assist in generating and updating project schedules, as it can learn from the data of past project performance. Then AI algorithms can predict task durations and resource needs,

which can help to create more realistic project schedules. Also, AI-based scheduling tools can optimize resources by matching the right people to the right tasks at the right time. As a result, this AI technology leads to better utilization of resources and adjustment of assignments in real-time as project conditions change (Nagireddy, 2023).

2.3.3 Predictive Analytics for Project Outcomes

the use of AI Machine learning models can forecast project outcomes, like final costs or completion dates, by analyzing historical project data and real-time metrics. This predictive Planning enables project managers to predict potential cost overruns or delays earlier and with greater accuracy. Therefore, this can support project managers to make proactive decisions, by adjusting scope or adding resources. Also, advanced AI technology can run simulations of project scenarios, giving managers insight into the results of different decisions that can help them navigate their projects (a sort of "virtual what-if analysis" powered by data).

2.3.4 Risk Identification and Management

AI is being applied by some organizations to improve risk management by using historical data for generating warning signs. Risk identification was done by using human developed checklists and now has been performed by AI systems that detect patterns linked to risk in project reports, schedules, or even external data such as economic indicators and weather forecasts). Studies such as the one conducted by (Savio & Ali, 2023) show that AI can analyze several datasets from past project archives, to flag potential risks that a human might overlook or cannot predict. For example, an AI tool might learn that specific design changes typically result in cost overruns and alert the PMO when such changes occur, providing early warnings and even prioritizing risks by estimated impact. AI also allows project managers and risk officers to plan mitigation measures for risks as data-driven approach enhances the traditional risk registers by continuously updating risk profiles as conditions evolve.

2.3.5 Automation of Routine PMO Tasks

Many tasks in project management such as status reports, issues tracking, updating dashboards, can be partially or fully automated using AI. For instance, natural language generation algorithms can make weekly status reports from raw project data, and chatbots can respond to team inquiries about project procedures or schedules. As a result, AI help to frees up project managers and PMO staff to focus on important tasks and activities that need human judgment, like stakeholder communication and team leadership. Automation also can help reduces human error in project records and ensures more timely updates are produced form the data (Fridgeirsson et al., 2023).

2.3.6 Intelligent Assistance and Communication

AI-powered virtual assistants, also sometimes called project chatbots or digital project assistants, are emerging to support project managers and teams. These assistants can answer questions about the project status or even interact with project management software on behalf of users. This technology uses natural language processing to understand queries and can operate 24/7, improving team communication and responsiveness. Additionally, AI can facilitate better collaboration by analyzing communication patterns in project teams such as emails and suggesting improvements or flagging potential issues in communication (Patil et al., 2025).

2.3.7 Impact and Emerging Trends

The effect of all these AI applications in a project environment that is more data-driven and proactive is notable. Predictive insights can now inform decisions that relied heavily on a manager's intuition and judgments. Routine process compliance checks, status updates, can be continuously monitored by AI, ensuring nothing falls behind. According to a Harvard Business Review analysis, the coming years will likely bring major shifts in the project management profession due to AI. By 2030, technology is expected to significantly enhance project selection and prioritization, automate progress tracking and reporting, and enable real-time testing and adaptation of project plans

In this expected future scenario, project managers' roles may evolve to focus less on micromanaging or monitoring and more on providing human leadership. Project managers can provide coaching for teams, manage stakeholders effectively, and make strategic decisions, as AI is handling routine and repetitive tasks. PMI and other professional bodies have launched initiatives such as “PMI's PMI x AI program” to explore the possibilities of AI adoption with project management practices. But this adopting of AI in project management comes with challenges, including data quality issues, change management, fear of change, and ethical considerations, and bias. However, research indicates that AI adoption in project management is gaining more attention globally from organization and academics and is expected to transform the field in the next decade (Adamantiadou & Tsironis, 2025).

In summary, AI can offer powerful tools and technology to help project managers and PMOs to improve forecasting accuracy, fast information processing, and informed decision-making. AI has the potential to increase project success rates if well implemented, by **reducing** uncertainties and inefficiencies that traditional project management techniques cannot easily address or predict. The global focus on AI to develop and adopt it is notable, as tech startups, large consulting firms, and even government initiatives, are investing and doing more experiments with AI-driven project management solutions, which will lead to a new era of smarter project delivery and more efficient PMOs.

2.4 AI in Construction Project Management

2.4.1 Applications in the Construction Industry

The construction sector is known for its labor-intensive and project-based nature, and complexity as projects are not similar although they might seem. Therefore, this industry is still lagging in integrating AI compared to other industry. But nowadays the interest in applying AI to improve project management and execution is increasing rapidly. Construction projects present complex challenges such as uncertain site conditions, evolving designs, and coordination of many stakeholders that generate large amounts of data. Construction sector started to notice its benefits on other sectors and as a result AI technologies are increasingly seen as key to leveraging this data and enhancing decision-making in construction projects. Recent systematic reviews indicate that AI applications in construction project management have concentrated mainly in the project planning phase and the monitoring and control phase of projects (Adebayo et al., 2025; Silitonga & Jin, 2024).

For example, in Planning construction projects AI techniques are used to optimize schedules, forecast costs, and refine project plans, while in monitoring. AI also can helps in resource allocations and track progress and detect issues in real time. Common benefits for AI in

construction include decision support, prediction, optimization, and performance improvement (Adebayo et al., 2025). In other words, AI is being employed to predict project outcomes which can help to optimize construction processes for better efficiency, quality and safety. All this can help to continually improve project execution and outcomes through data-driven feedback.

2.4.2 Examples of AI in construction management include:

Cost Estimation and Budgeting: Cost forecasting is a very crucial element in the construction sector as it is one of the major project constraints. In this regard, AI is transforming the way estimators and quantity surveyors to perform work. Traditionally, cost estimation relied on expert experience and manual models, which can be subjective, bias and error prone. AI methods, particularly machine learning, can analyze historical cost data from past projects to predicts cost as it can learn the complex relationships between project parameters such as design features, materials, market conditions. Some construction firms used Machine learning models, or regression models and neural networks to generate more accurate and consistent cost estimates early in the project lifecycle (G. Chen et al., 2025).

Some Studies have noted that intelligent cost estimating techniques significantly reduce the effort and time required by project teams and it also improves accuracy by minimizing human bias and error. For instance, an AI system can quickly evaluate thousands of similar past project data points to predict the cost, and also the impact of a design decision. Research in the UK found that while AI-based estimating is still in its early stages in construction, it is rapidly growing and seen as a key solution for handling the uncertainty in early-stage cost forecasts (Adebayo et al., 2025). Organizations are beginning to deploy AI-driven estimating tools or use existing estimation tools that are AI supported to continuously improve cost estimation, ultimately helping prevent budget overruns by more accurately predicting costs.

Scheduling and Site Management: Construction schedules are prone to delays due to factors like weather, materials delays, or on-site productivity or construction issues. AI algorithms can improve scheduling by analyzing historical schedule performance of similar projects, and real-time project data to predict possible delays or resource issues. For example, AI can integrate weather forecasts and crew productivity data to warn if a task is likely to slip, allowing project managers to re-sequence activities, allocate extra resources proactively or plan proper risk mitigation. In large projects, reinforcement learning algorithms have been experimented to find optimal construction sequences or crane movements, effectively learning the best way to construct a project through simulation (Sahadevan, 2023).

As a result, AI-based schedule optimization can therefore increase efficiency and reduce idle times of resources. Also, AI-powered tools sensors enable real-time monitoring of construction progress, and computer vision systems can compare daily site photographs or 3D laser scans against Building Information Modeling (BIM) to assess work completed to the plan which can help in flagging any deviations. This enhances the monitoring process by providing objective and valuable progress data rather than relying solely on periodic human inspections (Merdžanović et al., 2023).

Quality and Safety Management: Ensuring quality and safety are crucial in construction projects and one of its constraints. AI is being applied to these areas via technologies such as computer vision and pattern recognition. For quality control, AI systems can automatically

detect defects or inconsistencies in construction work by analyzing images. For example, identifying cracks in structures or incorrect installations captured in photos/drone footage and then the system compare it to the learning data that is been feed into his system (Luo et al., 2025). Similarly for safety, AI-driven video analytics can monitor site videos to recognize unsafe behaviors or conditions. Workers not wearing protective gear or equipment can be detected by the system such as computer visions and can alert supervisors in real time to prevent accidents (Waqar et al., 2023)

Additionally, predictive models that use AI have been used to foresee safety incidents by learning from past incident data. Also, some organizations use it to identify which combinations of factors or site conditions like schedule pressure, weather, and crew experience correlate with higher accident rates. By identifying high-risk situations in advance, project managers can apply more safety measures and lower accidents or accidents. This proactive risk management through AI is a developing area aimed at achieving zero-incident projects. (Shanti et al., 2021)

Design and Engineering Optimization: In project design, AI is aiding architects and engineers in the design phase, which indirectly benefits project management by reducing scope changes and the resulting downstream from these design changes. Some AI techniques like generative design, powered by AI algorithms, can rapidly produce and evaluate numerous design alternatives under given constraints, allowing optimal solutions for cost, sustainability, resources and construction method to be used. It means that before construction begins, AI helps in value engineering, finding best possible design approaches that meet project objectives and customer needs at lower cost or risk.

Moreover, AI in the form of structural optimization algorithms can ensure that materials are used efficiently, schedules are realistic, and potential construction difficulties are discovered in the design stage, therefore minimizing costly changes and delays during construction. For example, AI can analyze data from various sources like smart devices and BIM system to identify patterns in construction performance and usage, for future construction needs (Egwim et al., 2023).

Industry 4.0 and Future Trends: Construction 4.0 is moving forwards to digitization of construction and by the integration of AI technologies like, IoT, Big Data, robotics, and more. AI is become one of the core technologies driving this transformation of construction globally. Many industry bodies are developing strategies to integrate AI into construction processes as part of digitizing the sector. Recent research show a rapid increase in studies on AI in construction, with the United States, UK, and China among the leaders in publication output, and they underscoring the global scope of interest and they concluded that the impact of AI has begun to make is significant as it is revolutionizing the industry; offering innovative solutions to enhance efficiency, reduce costs, and improve decision making in construction project management (Adebayo et al., 2025).

Empirical analyses of AI use in construction discovered that employing AI leads to improved performance especially in terms of time and cost savings and better adherence to project specifications and requirements (Adebayo et al., 2025). For example, machine learning models that optimize equipment usage can cut idle time and save energy, while AI-driven predictive maintenance for construction machinery can prevent breakdowns that might stop a project. Furthermore, the integration of AI with other advanced technologies, such as the

IoT and BIM, forms a robust digital ecosystem that enhances data collection, analysis, and make actionable insights for proactive project management (H.-P. Chen & Ying, 2022).

Also, several AI-related trends are already influencing construction project management: Digital twins allow AI to run simulations and optimizations continually during project execution. Advanced robotics and autonomous machines may handle repetitive or hazardous construction tasks such as bricklaying robots or autonomous earthmoving equipment with AI systems ensuring they operate safely and efficiently alongside human workers.

AI is also being applied to sustainability goals in construction – for instance, optimizing energy use on worksites or designing buildings for lower lifecycle energy consumption is aligning with the industry's aim for greener projects (Adebayo et al., 2025). Furthermore, as data from various sources, drones, sensors, smart devices, becomes more valuable on construction sites, Big Data analytics in combination with AI will play a bigger role in integrating information and providing actionable insights to project managers. Despite the promises AI can provide, the construction industry's adoption of AI is still in its early stages. Many firms are piloting AI tools on a small scale and challenges such as data quality, lack of AI expertise in organizations, and the need for change management are being observed and addressed gradually. Therefore, case studies and research consistently show that AI can be a powerful to improve construction project outcomes as it can help in reducing cost overruns, enhancing safety, AI's contributions align closely with the objectives of project management in construction.

In summary, as the construction industry undergoes a digital transformation, project management offices (PMOs) and project managers are increasingly embracing AI-driven tools to boost planning, streamline project execution, and deliver better project outcomes. The evolution of both AI and PMO methodologies is converging in this sector, empowering modern construction teams to benefit from data-driven insights, automate complex tasks, and proactively manage risks. As Integrating AI throughout the project lifecycle, today's PMOs can set new standards for efficiency, adaptability, and success in construction project management.

2.5 Previous Studies

In this section, we review ten relevant studies from around the globe on the use of Artificial Intelligence (AI) in project management offices (PMOs) and the construction industry, including each study's location and key outcomes. This overview highlights the current research landscape, spanning systematic literature reviews and empirical investigations, to identify common findings and gaps in this domain.

2.5.1 Bento et al. (2022) – AI for Efficiency in Project Management

Study Location: Portugal (literature review of global studies)

Study Outcome: Bento and colleagues conducted a systematic review of AI in project management and found that AI implementation can significantly improve project efficiency and precision, leading to notable cost reductions and shorter delivery times (Bento et al., 2022). Their analysis indicated that AI-driven tools (e.g. predictive analytics and machine learning systems) enhance decision-making and real-time project control, thereby enhancing overall project performance in sectors like construction. This review

underscored AI's potential to streamline processes such as scheduling and forecasting. However, it also noted the need to address challenges (like data requirements and change management) to fully realize these benefits (Bento et al., 2022).

2.5.2 Hashfi & Raharjo (2023) – AI's Impact Across PMBOK Process Groups

Study Location: Indonesia (literature review of global studies)

Study Outcome: Hashfi and Raharjo performed a systematic literature review mapping AI's challenges and impacts onto the Project Management Body of Knowledge (PMBOK) process groups (Hashfi & Raharjo, 2023). Their findings show that AI tools enhance multiple project management activities: in the Initiating phase, AI improves risk assessment and cost prediction; in Planning, it aids in project selection, cost estimation, resource allocation, and decision-making (Hashfi & Raharjo, 2023).

During execution, advanced AI techniques (e.g., machine learning algorithms) boost productivity and resource utilization while reducing costs and supporting faster decision-making. In Monitoring and Controlling, AI systems (such as real-time analytics and anomaly detection) increase efficiency, improve quality control, and provide timely decision support (Hashfi & Raharjo, 2023). Even in Closing, AI helps optimize resource handover and minimize waste. Overall, this review highlights that AI integration can lead to more agile and data-driven project management practices across all phases of a project's lifecycle, while also emphasizing the importance of organizational readiness to overcome adoption barriers.

2.5.3 Regona et al. (2022) – AI Adoption Challenges in Construction

Study Location: Australia (PRISMA-based literature review of global construction industry studies)

Study Outcome: Regona and co-authors examined the opportunities and adoption challenges of AI in the construction industry. Their review revealed that despite AI's touted benefits, the construction sector has been slow in embracing these technologies (Regona et al., 2022).

They found that AI adoption in construction projects remains relatively limited compared to sectors like finance and manufacturing (Regona et al., 2022). Key opportunities identified include AI's ability to improve project outcomes (e.g., schedule optimization, cost efficiency, and safety monitoring). However, numerous barriers are hindering widespread implementation in construction: issues with integrating AI into existing systems and processes, the high cost of AI solutions, resistance to change among stakeholders, and concerns about data quality and privacy (Regona et al., 2022). The study underscores that addressing these challenges – through better data strategies, change management, and cost-benefit clarity – is crucial for construction organizations to capitalize on AI-driven improvements in project delivery.

2.5.4 Adebayo et al. (2025) – Applications and Trends of AI in Construction PM

Study Location: United Kingdom & Nigeria (structured literature review of global research)

Study Outcome: Adebayo and colleagues conducted a comprehensive structured literature review on AI in construction project management, analyzing 135 peer-reviewed articles

from 1985 to 2024(Adebayo et al., 2025). Their study found that AI technologies are most applied during the Project Planning and Monitoring/Control phases, where tools like predictive modeling and computer vision enhance decision-making, forecasting, and performance tracking(Adebayo et al., 2025). Predominant purposes of AI usage include decision support, risk prediction, schedule optimization, and overall performance improvement. They identified several drivers for AI adoption in construction, such as the availability of advanced technology, the need for better project outcomes (time, cost, quality), competitive advantage pressures, and sustainability goals (Adebayo et al., 2025).

At the same time, the review highlighted persistent barriers like those found by Regona et al.: difficulties in data integration, high implementation costs, stakeholder resistance to technological change, and ethical concerns (for example, around data privacy)(Adebayo et al., 2025). Notably, the researcher also pointed to emerging future trends in construction AI, including the use of digital twins, autonomous robotics on job sites, and AI for energy efficiency and sustainability improvements (Adebayo et al., 2025). This study provides a global perspective that while AI is revolutionizing construction project management by improving efficiency and decision quality, organizations must navigate adoption hurdles to fully leverage these innovations.

2.5.5 Fridgeirsson et al. (2021) – Future Impact of AI on PM Knowledge Areas

Study Location: Iceland (survey of project management experts internationally)

Study Outcome: Fridgeirsson and colleagues carried out an authoritative study exploring how AI will augment the project management profession over the next decade, focusing on the ten PM knowledge areas defined by PMI's PMBOK(Fridgeirsson et al., 2021). Through a survey of experienced project managers worldwide, the study found consensus that AI will become an integrated part of future project management practices, with a powerful impact anticipated in the knowledge areas of Cost Management, Schedule Management, and Risk Management (Fridgeirsson et al., 2021). Respondents indicated that AI excels in processes where historical data informs Planning and estimation. For example, AI can accurately forecast project costs and durations, monitor schedules in real time, adjust forecasts as conditions change, and help maintain baselines by flagging deviations (Fridgeirsson et al., 2021). The results suggest that AI-driven analytics will significantly aid in identifying and mitigating risks, thus improving on-time and on-budget delivery. However, the study also concludes that AI's impact will be far less in areas requiring human judgment and leadership, such as team building, stakeholder management, and other domains demanding emotional intelligence (Fridgeirsson et al., 2021). In summary, experts believe AI will augment project managers by automating analytical and routine tasks, thereby allowing professionals to focus on strategic and people-oriented aspects that AI cannot replicate.

2.5.6 Shanti et al. (2021) – AI-Driven Construction Safety in the UAE

Study Location: United Arab Emirates (case implementation on construction sites)

Study Outcome: Shanti and co-researchers presented a novel implementation of an AI-based "smart" safety inspection system for construction projects in the UAE. The AI model (leveraging computer vision and deep learning) was designed to automatically detect safety violations on site (such as workers missing protective equipment or unsafe conditions) in

real time. The implementation's results were highly promising: the AI system achieved an accuracy of over 91% with approximately 99% precision in identifying safety issues, and a recall rate of about 90% (Shanti et al., 2021). These performance metrics indicate that the model can reliably recognize most hazards or non-compliance incidents on construction sites. The study's outcomes verify the effectiveness of AI in enhancing construction safety monitoring, as the system was able to control potential violations proactively and help avoid accidents before they occurred (Shanti et al., 2021). Practically, this means project managers and PMOs in construction can deploy AI-driven surveillance to significantly reduce on-site risks, improve compliance with safety regulations, and protect workers – outcomes that not only save lives but also prevent costly schedule disruptions due to accidents. This case exemplifies how AI tools can deliver tangible improvements in construction project performance (through risk reduction and increased safety), especially in fast-developing regions like the Middle East that are investing in innovative construction technologies.

2.5.7 Luo et al. (2025) – AI Assimilation and Performance in Chinese Construction

Study Location: China (quantitative survey of construction firms)

Study Outcome: Luo and co-authors investigated how the internal adoption of AI ("AI assimilation") within construction companies influences organizational performance under innovative business models. Their study surveyed 174 practitioners in China's construction industry and analyzed the data using structural equation modeling (PLS-SEM). The results demonstrate that exploratory innovation (i.e., a firm's pursuit of new ideas and technologies) significantly improves company performance through AI assimilation. In other words, firms that are more innovative and better at integrating AI into their processes see enhanced project outcomes and efficiency (Luo et al., 2025).

Likewise, adopting novel business models works synergistically with AI, as new business approaches promote deeper AI utilization, which in turn drives performance gains (Luo et al., 2025). Interestingly, the study also found that competitive market intensity plays a moderating role: in highly competitive environments, the positive effect of exploratory innovation on AI assimilation becomes stronger, but the direct contribution of AI assimilation to performance gains is somewhat weakened (Luo et al., 2025).

This approach suggests that while AI integration generally boosts construction project performance (for example, through better cost control and innovation), fierce competition can dampen the immediate performance returns, perhaps due to rapidly shifting benchmarks or the need for complementary capabilities. Overall, Luo et al.'s research in China provides empirical evidence that embracing AI alongside innovative practices can yield significant improvements in construction project success metrics. However, organizations must also consider market conditions in strategizing their AI investments (Luo et al., 2025).

2.5.8 Abioye et al. (2021) – AI Applications and Challenges in Construction

Study Location: United Kingdom (critical literature review with global scope)

Study Outcome: Abioye, Oyedele, Akanbi, Ahmed, and colleagues performed a critical review of the current status, opportunities, and challenges of AI applications in the construction industry (Abioye et al., 2021). This UK-led study noted that the construction sector faces myriad complex challenges (chronic cost/time overruns, safety issues, labor shortages, etc.), and that AI – through subfields like machine learning, knowledge-based

systems, computer vision, robotics, and optimization algorithms – has the potential to address many of these issues (Abioye et al., 2021).

The authors reviewed how AI techniques have been successfully applied in other industries and identified key construction-specific AI applications already in use or development. These include activity monitoring on sites (e.g., using drones or cameras with AI to track progress and safety), risk management (AI models predicting project risks or failures), and resource/waste optimization (algorithms improving resource allocation and minimizing material waste)(Abioye et al., 2021). Alongside cataloguing these applications, the study outlined the opportunities that AI offers – such as increased productivity, improved safety, and enhanced decision-making – and the challenges that still exist in realizing these benefits. Challenges mentioned include the construction industry's low level of digitization, lack of AI expertise among practitioners, data availability and quality issues, and organizational resistance to adopting new technologies(Abioye et al., 2021).

Abioye et al. conclude with insights into pathways for the industry to capture the accruable benefits of AI, urging stakeholders to invest in digital infrastructure, training, and change management. This review thus provides a roadmap of how AI can be leveraged to overcome persistent construction project management hurdles, while cautioning about the preparatory work needed to diffuse AI innovations successfully.

2.5.9 Kumar et al. (2021) – Practitioner Perspectives on AI as a Success Factor

Study Location: India (qualitative study with global expert interviews)

Study Outcome: Kumar, Pandey, and Singh explored whether AI is perceived as a critical success factor for construction projects by experienced project practitioners (Kumar et al., 2021). Through semi-structured interviews with senior project managers from large construction projects worldwide, the researchers gathered insights into how practitioners view AI in relation to project success. The findings reveal a somewhat cautious stance among veteran project managers. Interviewees generally acknowledged AI's potential to improve project performance (for example, by automating routine tasks or improving data analysis), but do not yet see AI as a decisive success factor on par with traditional factors like effective leadership or stakeholder management.

The study highlights several perceived drawbacks of current AI technologies from the practitioner viewpoint: (i) AI systems lack soft skills and emotional intelligence, (ii) they lack the flexible human-like reasoning needed to interpret ambiguous situations, and (iii) they cannot replicate the relationship-building and people management capabilities that project managers use to drive project success (Kumar et al., 2021).

The consensus was that AI, as of now, remains a set of advanced tools distinct from conventional project management software, and is "still years away" from developing any form of self-awareness or human-like judgment(Kumar et al., 2021).

Thus, while AI can support project managers (for instance, through better data insights), these practitioners believe that successful project delivery still relies primarily on human expertise and leadership. This study provides an important practical perspective: in the eyes of top project managers, AI is an enabler but not a substitute for the human elements critical to project success, at least with today's technology.

2.5.10 Salimimoghadam et al. (2025) – Opportunities and Barriers of AI in Project Management

Study Location: Australia (systematic literature review of global project management research)

Study Outcome: Salimimoghadam and colleagues conducted a recent systematic literature review (published in Buildings 2025) examining current opportunities, enablers, and barriers related to implementing AI and machine learning in project management (Salimimoghadam et al., 2025). This review synthesizes a fragmented body of literature to present a comprehensive framework for AI adoption in project settings. The findings highlight several transformative benefits of AI for project management. For example, AI technologies dramatically improve forecasting accuracy (such as more reliable schedule and cost predictions), enhance risk mitigation through advanced analytics, facilitate better stakeholder collaboration (e.g., via AI-driven communication and knowledge management tools), and strengthen safety management on projects (Salimimoghadam et al., 2025).

These advantages align with other studies, reinforcing that AI can optimize resource allocation and automate routine processes, leading to more efficient and informed project execution. On the other hand, the review also identifies critical challenges and barriers. Chief among these are the difficulties of integrating AI solutions with legacy systems already in use by organizations, problems with data quality and availability that can undermine AI insights, and organizational resistance to change (including workforce apprehension about AI)(Salimimoghadam et al., 2025). The authors note that specific enablers – like top management support, staff training, and a strong data governance framework – can help overcome these barriers. This study's outcome is a balanced outlook: while AI holds immense promise to reshape project management practices across industries (making them more data-driven and proactive), success largely depends on how well organizations manage the adoption process, address technical and cultural hurdles, and capitalize on the enablers that make AI implementation viable and effective.

2.5.11 Summary of past studies:

Each of these studies contributes to a growing understanding that AI is gradually becoming an integral part of project management and PMO functions, particularly in data-intensive sectors like construction. Overall, they illustrate that AI can offer substantial efficiency improvements, such as optimizing scheduling and forecasting, reducing costs, and enabling faster decision-making through predictive analytics (Bento et al., 2022). They also highlight AI's capacity to enhance risk management and overall project outcomes. At the same time, this body of work converges on the notion that realizing AI's full potential requires overcoming significant adoption challenges, including issues with data quality and integration, high implementation costs, and organizational resistance to change(Regona et al., 2022).

This research emphasizes that human expertise remains crucial, with AI functioning primarily as a tool to enhance the capabilities of project managers. By automating routine tasks and offering data-driven insights, AI allows human leaders to focus on complex decision-making and the essential "soft skills" that are vital for project success. (Bento et al., 2022; Luo et al., 2025). This comprehensive review of prior work thus sets the stage for further research into strategies for effectively blending AI tools with project management best practices to enhance success in construction and beyond.

2.6 Theoretical framework

This study is grounded in two complementary theoretical models: the Diffusion of Innovations Theory [Rogers, E. M.. *Diffusion of Innovations* (5th ed.). Free Press.] and the Technology Acceptance Model [Davis, F. D.. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13, 319-340.]. These theories collectively provide a robust foundation for understanding the mechanisms behind the adoption and integration of Artificial Intelligence within Project Management Offices in the construction sector.

The **Diffusion of Innovations Theory**, as developed by Everett Rogers, explains how new technologies spread across social systems over time. It highlights five critical factors influencing the adoption process: relative advantage, compatibility, complexity, trialability, and observability. Within this framework, AI adoption in construction PMOs can be seen as a process progressing through the stages of knowledge, persuasion, decision, implementation, and confirmation. By applying DOI, the study explores how organizational factors, communication structures, and the perceived characteristics of AI — such as its **relative advantage in automating complex construction schedules or improving safety compliance**, or its **complexity when integrating with existing Building Information Modeling systems** — influence the rate and success of its diffusion within dynamic construction project environments. This macro-level perspective helps identify the organizational conditions conducive or detrimental to AI integration.

In parallel, the **Technology Acceptance Model** adds an individual-level perspective, focusing on how users' perceptions shape their intention to use AI tools. It centers on two key constructs: Perceived Usefulness and Perceived Ease of Use, which jointly determine user acceptance. This model helps explain how PMO team members and stakeholders in construction evaluate AI systems in terms of their **perceived usefulness for tasks like precise cost estimation or risk prediction specific to construction projects**, and their **perceived ease of use given varying levels of digital literacy within construction teams**. Their willingness to adopt and engage with the technology, therefore, directly impacts individual-level integration.

By integrating DOI and TAM, this research can comprehensively analyze AI integration by understanding how macro-level organizational factors create an environment that shapes individual perceptions and intentions. For example, strong organizational readiness (a DOI-related factor) might lead to better training and support, thereby enhancing users' perceived ease of use, which in turn accelerates broader organizational diffusion. This combined approach offers a nuanced understanding of success factors and challenges in AI adoption within construction PMO contexts. This study combines these two theoretical perspectives to investigate:

- **Independent Variable:** AI Integration into Project Management Office Functions.
- **Dependent Variable:** PMO Effectiveness and Strategic Value Contribution.

The third includes **moderating variables** that can impact the relationship between AI integration and PMO effectiveness:

- **Organizational readiness:**
- **Change management practices:** (Moderates as it facilitates or hinders the implementation and acceptance process, aligning with both DOI's implementation stage and TAM's user acceptance)
- **Ethical barriers:** (Moderates by affecting the 'decision' stage of DOI and potentially undermining 'perceived usefulness' in TAM if concerns are high)
- **Technical barriers:** (Moderates by directly impacting 'perceived ease of use' in TAM and 'complexity' in DOI, thus slowing or preventing successful integration)

These moderating variables are considered because they can influence the strength and nature of how AI integration affects PMO effectiveness and strategic value. For instance, high organizational readiness and effective change management are expected to strengthen the positive impact of AI integration, while significant technical or ethical barriers are likely to weaken it.

This theoretical foundation supports the empirical investigation and guides the development of hypotheses and analysis tools to examine how AI affects project governance, decision-making, resource management, and overall project performance in construction PMOs. This combined theoretical approach allows for a nuanced understanding of both the macro-level dissemination of AI technologies across organizations and the micro-level acceptance by individual users.

Chapter Three: Study Methodology

3.0 Introduction:

This chapter outlines the research methodology employed to investigate the effect of integrating Artificial Intelligence (AI) into Project Management Office (PMO) tasks and tools in the construction sector. It describes the overall research approach and strategy, defines the target population and sampling method, details the data collection instrument and analysis procedures, and addresses ethical considerations and study limitations.

3.1 Research Design

The research adopts a descriptive-analytical and exploratory design. This approach facilitates a comprehensive understanding of the integration of Artificial Intelligence (AI) into Project Management Office (PMO) tasks and tools in the construction sector. It draws on a systematic review of previous studies to establish a solid theoretical foundation and identify existing knowledge gaps, while also employing quantitative methods through survey questionnaires to gather empirical data from industry practitioners. This dual approach enables the study to analyze both conceptual perspectives and real-world practices, assessing the impact of AI integration on PMO performance, governance, and strategic value. By combining insights from literature review findings with survey-based evidence, the research strengthens the validity of its conclusions and provides a balanced view of the opportunities and challenges associated with AI adoption in construction project management.

3.2 Population of the Study

The population for this study comprises Project Management Office (PMO) professionals and project management practitioners operating within the construction sector. This includes individuals working in organizations that have already implemented, or are in the process of implementing, Artificial Intelligence (AI) tools and systems to enhance PMO functions and project delivery. The target population specifically covers PMO managers, project managers, project coordinators/specialists, planners, schedulers, and other stakeholders directly involved in governance, decision-making, and operational activities within construction projects. By focusing on this group, the study ensures that the collected data reflects the perspectives and experiences of professionals who are most affected by, and directly engaged with, the integration of AI into PMO tasks and tools in the construction industry.

3.3 Sample Characteristics

The sample for this study comprises professionals working in the construction sector who are directly involved in project management or PMO functions. Participants include PMO directors and managers, portfolio and program managers, project managers, senior executives, superintendents, site managers, engineers, and other specialists engaged in construction project delivery. The organizations represented in the sample undertake diverse types of construction projects, such as commercial, residential, industrial, infrastructure, healthcare, educational, and government facilities.

To ensure relevance, participants are selected based on their active involvement in PMO operations and their familiarity with digital tools, AI-enabled solutions, or decision-making processes in construction projects. This includes individuals with varying levels of professional certifications (e.g., PMP, PgMP, PfMP, RMP) and experience ranging from less

than 2 years to more than 15 years in construction project management. The diversity of roles, project types, and experience levels ensures that the data collected reflects a comprehensive view of AI integration opportunities, challenges, and impacts across construction PMOs.

3.4 Sample Size Determination

The sample size for this research is determined using purposive sampling to specifically target professionals with relevant expertise in Project Management Office (PMO) operations and construction project management. The study initially aimed to gather responses from at least 50 professionals working within the construction sector, ensuring adequate representation across different organizational roles, experience levels, and project types. This sample size was chosen to provide sufficient data for meaningful statistical analysis while capturing diverse perspectives on AI integration challenges and opportunities in construction PMOs.

While the targeted number of responses has not yet been fully achieved, the purposive selection strategy ensures that participants possess direct, practical knowledge of AI tools, digital transformation initiatives, and PMO governance in construction. This focus enhances the relevance and applicability of the findings to the sector.

3.5 Data Collection Procedures

The study utilizes a multi-method approach focused on quantitative and secondary data sources which are:

1. **Quantitative Data:** A structured online survey questionnaire was developed and distributed to professionals working in Project Management Offices (PMOs) and construction project management roles. The survey aims to capture participants' perspectives on the integration of Artificial Intelligence into PMO tasks and tools, including perceived benefits, challenges, and potential opportunities. The questionnaire includes both closed-ended and scaled questions to enable statistical analysis of trends, correlations, and patterns within the construction sector.
2. **Secondary Data:** A comprehensive review of relevant peer-reviewed literature, industry reports, and case studies was conducted to provide contextual background and strengthen the interpretation of survey findings. This review covers global and sector-specific studies on AI adoption in PMOs, AI applications in construction, and related organizational and technological challenges.

This approach ensures that the research findings are grounded in both empirical survey data and existing scholarly and industry evidence, allowing for a more robust and nuanced understanding of the research problem. While survey data collection is still in progress, the current methodology remains aligned with the study's objectives and research design.

3.6 Study Determinants

1. **Temporal Boundaries:** This study examines the integration of Artificial Intelligence into Project Management Office (PMO) tasks and tools in the construction sector,

focusing primarily on research and practical implementations observed over the past five to ten years. This period aligns with the period in which most of the reviewed studies were conducted, offering both historical context and contemporary insights into AI adoption trends, challenges, and benefits for PMOs in construction.

2. **Geographical Boundaries:** The research focuses on the construction sector with a particular emphasis on organizations operating in the Middle East, while also considering relevant global studies to provide a comprehensive perspective. This geographical scope ensures that findings reflect both local industry dynamics and international best practices in AI integration.
3. **Subject Boundaries:** The study is confined to examining the effect of AI integration on PMO functions and tools in the construction sector, specifically in relation to governance, decision-making, portfolio optimization, and operational efficiency. It addresses both the opportunities and challenges associated with AI adoption, with particular attention to technical, organizational, and ethical considerations.
4. **Limitations:** One limitation of the study is the smaller-than-anticipated survey sample size due to difficulties in securing responses from targeted construction PMO professionals. While the intended sample aimed to provide broader statistical representation, the available responses still offer valuable qualitative and quantitative insights but may limit the generalizability of some findings.

3.7 Method of Analysis

The quantitative data collected from the survey will be analyzed using **SPSS** (Statistical Package for the Social Sciences) or alternatively, Python-based statistical libraries such as **pandas**, **NumPy**, and **scikit-learn**. The analysis will include descriptive statistics to summarize the data, correlation analysis to examine relationships between variables, and regression analysis to test the research hypotheses related to the impact of AI integration on PMO effectiveness in the construction sector.

As the study does not involve qualitative interviews, the analysis will focus exclusively on quantitative techniques, supplemented by secondary data interpretation from reviewed literature. Statistical results will be presented in tables and charts for clarity, and findings will be interpreted in the context of the Diffusion of Innovations (DOI) and Technology Acceptance Model (TAM) frameworks to provide theoretical grounding. This analytical approach ensures rigorous testing of the hypotheses while enabling data-driven insights into the opportunities and challenges associated with AI adoption in construction PMOs.

3.8 Methodology and Research Methods

3.8.1 Study Phases

Phase 1- Literature Review: A comprehensive literature review was conducted to establish the theoretical foundation for the study. This review focused on peer-reviewed articles, doctoral dissertations, and authoritative industry reports related to Artificial Intelligence (AI) integration, Project Management Offices (PMOs), and construction sector applications. The process identified key concepts, challenges, and opportunities, as well as gaps in existing research, particularly in the application of AI within PMO functions. Insights from this phase guided the design of the survey instrument and shaped the research hypotheses.

Phase 2- Quantitative Survey Analysis: Based on the findings from the literature review, a structured survey questionnaire was developed and distributed to PMO professionals and project management practitioners in the construction sector. The survey aimed to collect quantitative data on the perceived impact of AI integration on PMO functions such as governance, decision-making, portfolio optimization, and task automation. Key metrics included improvements in functional effectiveness, efficiency, and strategic value delivery.

3.8.2 Study Tools:

1. **Literature Review** – Served as the theoretical base for the study, identifying best practices, challenges, and research gaps regarding AI integration in PMOs, specifically within the construction sector.
2. **Survey Questionnaire** – Structured to capture the perceptions, experiences, and expectations of construction PMO professionals regarding AI adoption. The instrument was designed to quantify both opportunities and challenges, aligned with the research hypotheses.
3. **Secondary Data Review** – Complementary data were drawn from published studies, industry reports, and standards issued by organizations such as PMI, providing context and supporting the interpretation of survey findings.

This methodology allows for a data-driven analysis of AI's effect on PMO tasks and tools in construction, combining theoretical insights from existing literature with empirical evidence from sector professionals.

3.9 Research Community

The research community for this study comprises professionals working in Project Management Offices (PMOs) and project management roles within the **construction sector**. This focus was selected due to the sector's central role in delivering large-scale, high-value projects that require advanced project governance, strategic planning, and efficient resource management.

Within these organizations, the study targets individuals directly engaged in PMO-related functions and decision-making processes, including **PMO Managers, Project Managers, Project coordinators/specialists, Other Key Stakeholders** involved in project oversight and governance.

These professionals are well-positioned to provide practical insights into the **challenges and opportunities** associated with integrating Artificial Intelligence (AI) into PMO tasks and tools. Their expertise is critical to understanding how AI adoption impacts areas such as governance, decision-making, portfolio optimization, and task automation within the construction industry.

The **survey questionnaire** distributed for this study is designed to capture respondents' perceptions, experiences, and expectations regarding AI integration. By focusing on PMO professionals in the construction sector, the study ensures that findings are both contextually relevant and directly applicable to the operational and strategic needs of this high-demand industry.

To ensure the integrity and accuracy of construct measurement, all survey items were systematically mapped to their corresponding theoretical constructs using a structured coding key. Each construct—such as PMO Effectiveness and Strategic Value, AI Integration and Adoption, Technical Barriers, Organizational Barriers, Opportunities and Perceived Benefits, and Future Outlook—was defined through a set of items reflecting its conceptual domain. Also, each of these codes aligns with and supports the research hypothesis, which posits that the integration of AI into PMO tasks and tools significantly influences project management outcomes within the construction sector. The selection of expert participants, the structure of the survey, and the identified limitations all serve to frame and test this hypothesis by situating findings within the realities of organizational practice, sector-specific constraints, and varying degrees of digital readiness. By explicitly linking methodological choices and contextual boundaries to the research hypothesis, the study reinforces the credibility and relevance of its conclusions.

This targeted approach provides a grounded and contextually relevant perspective on AI adoption within environments that are inherently characterized by complex project requirements, stringent timelines, multidisciplinary coordination, and elevated stakeholder expectations. By focusing on these real-world operational conditions—where uncertainty, risk, and performance accountability converge, the research ensures that its findings are not only theoretically insightful but also practically applicable. As such, the results offer meaningful contributions to both academic literature and professional practice, particularly in advancing the strategic role of PMOs and enhancing decision-making, governance, and quality outcomes in the construction sector.

3.10 Research Limitations

1. **Generalizability:** The findings of this study may be limited to the construction sector in Saudi Arabia, specifically within organizations that operate Project Management Offices (PMOs). This contextual focus may restrict the applicability of results to other industries or regions with different operational and organizational dynamics.
2. **Sample Size and Representation:** The ability to generalize results is further constrained by the limited number of survey responses obtained to date. Although efforts are ongoing to increase participation, the smaller-than-expected sample size may affect the statistical power of the analysis.

3. **Access to Data:** Full access to comprehensive project documentation and internal PMO performance data from participating organizations is not always possible due to confidentiality policies. This may limit the depth of certain analyses and reduce opportunities for data triangulation.
4. **Organizational Readiness Variations:** Differences in the level of digital maturity, change management practices, and readiness for AI adoption among participating organizations could influence the study's findings, introducing variability in observed outcomes.
5. **Ethical Considerations:** The study strictly adheres to ethical research principles, including informed consent, confidentiality, and secure data handling. While necessary, these safeguards may limit the scope of data collected, especially in areas involving sensitive operational information.

Despite these limitations, the research is expected to provide valuable insights into the integration of Artificial Intelligence into PMO functions in the construction sector, offering practical recommendations and contributing to the evolving understanding of technology adoption in project management.

Chapter Four: Conclusions and Recommendations

4.1 Introduction

This chapter presents the empirical analysis of the research data, structured to test the hypotheses formulated in Chapter 1. The core objective is to examine how the integration of Artificial Intelligence (AI) influences Project Management Office (PMO) effectiveness in the construction sector, and to explore the role of organizational and technical barriers in shaping this relationship. Specifically, this chapter evaluates both the direct effects of AI adoption on PMO outcomes and the potential moderating impact of barriers on this relationship.

The data analysis approach follows a structured sequence. First, the survey data is cleaned and the composite constructs are computed based on the item coding framework defined in the instrument design (see Chapter 3 and coding key). Each construct—representing key variables such as AI Integration, PMO Effectiveness, Barriers, Strategic Benefits, and Future Outlook—is tested for internal consistency and summarized descriptively. Second, inter-construct relationships are assessed through Pearson correlation coefficients. Third, multiple linear regression analyses are conducted to evaluate Hypotheses H1 through H4, examining the effect of AI integration on project-related outcomes and the role of barriers as predictors. Finally, Hypothesis H5 is tested using interaction models to explore whether technical and organizational barriers moderate the relationship between AI integration and PMO effectiveness.

All statistical tests are based on a final dataset of 51 valid observations, using a 3-point Likert scale as the response format. While the limited scale and sample size impose constraints on statistical power and measurement sensitivity, the analysis yields actionable insights. The results are interpreted in alignment with the study's conceptual framework, which integrates perspectives from the Technology Acceptance Model (TAM), the Diffusion of Innovation (DOI) theory, and organizational change management literature.

4.2 Measures and Construct Validity

To empirically test the proposed hypotheses, this study measured six latent constructs derived from the survey instrument, each operationalized through multiple Likert-type items. These constructs are: PMO Effectiveness and Strategic Value, AI Integration and Adoption, Technical Barriers, Organizational Barriers, Opportunities and Perceived Benefits, and Future Outlook. Each construct was coded using a 3-point Likert scale (Agree = 3, Neutral = 2, Disagree = 1), and composite scores were calculated as the arithmetic means of their corresponding item responses. The item-to-construct mapping was guided by the coding framework detailed in the research design and aligned with the uploaded coding key. Item-to-variable alignment was validated using token-based similarity matching to ensure accurate construct operationalization. To assess the internal consistency of each construct, Cronbach's alpha coefficients (α) were computed. While some constructs demonstrated modest reliability (e.g., Opportunities and Perceived Benefits: $\alpha = 0.598$), others fell below the commonly accepted threshold (e.g., AI Integration and Adoption: $\alpha = 0.292$). These lower values are attributable to the use of short subscales and a 3-point response format, which inherently compresses variance and limits internal consistency. Despite this limitation, all

constructs were retained to preserve the theoretical integrity of the model. Table 4.1 summarizes the number of items, Cronbach's alpha values, mean scores, standard deviations, and number of valid cases for each construct.

Construct (Code)	Items	α	Mean	SD	N
PMO Effectiveness & Strategic Value	9	0.373	2.118	0.337	51
AI Integration & Adoption	6	0.292	1.931	0.383	51
Technical Barriers	5	0.514	2.102	0.467	51
Organizational Barriers	5	0.296	2.090	0.422	51
Opportunities & Perceived Benefits	6	0.598	2.114	0.464	51
Future Outlook	3	0.431	2.288	0.538	51

Table 4.1: Construct Summary (Cronbach's α , Mean, SD, N)

4.2 Correlation Analysis

Before proceeding with regression-based hypothesis testing, bivariate relationships among the study's main constructs were explored using Pearson correlation coefficients. This preliminary step allows for an initial understanding of the direction and strength of associations between variables, as well as an assessment of potential multicollinearity or redundancy that could affect regression model stability.

The analysis included the six composite constructs derived from the survey: PMO Effectiveness and Strategic Value, AI Integration and Adoption, Technical Barriers, Organizational Barriers, Opportunities and Perceived Benefits, and Future Outlook. All constructs were computed as the arithmetic mean of their constituent items, as described in Section 4.2. Correlations were computed using pairwise deletion and are summarized in Table 4.2 below.

	PMO Effectiveness Strategic Value	AI Integration Adoption	Technical Barriers	Organizational Barriers	Opportunities Benefits	Future Outlook
PMO Effectiveness Strategic Value	1	0.288	0.298	0.299	0.389	0.35
AI Integration Adoption	0.288	1	0.148	-0.167	0.167	0.179
Technical Barriers	0.298	0.148	1	0.297	0.367	0.46
Organizational Barriers	0.299	-0.167	0.297	1	0.277	0.459
Opportunities Benefits	0.389	0.167	0.367	0.277	1	0.543
Future Outlook	0.35	0.179	0.46	0.459	0.543	1

Table 4.2: Pearson Correlation Matrix among Constructs

The results reveal several noteworthy patterns. First, PMO Effectiveness and Strategic Value is positively correlated with AI Integration and Adoption ($r = 0.288$), Opportunities and Perceived Benefits ($r = 0.389$), and Future Outlook ($r = 0.350$). These values suggest that respondents who perceive higher AI adoption also tend to view their PMOs as more strategically valuable and effective, aligning with the expectations of Hypothesis H1. Likewise, respondents who report optimism about the future role of AI (captured in the Future Outlook construct) also tend to associate AI with tangible benefits, reflected in the moderate positive correlation with Opportunities and Benefits ($r = 0.446$).

Interestingly, both Technical Barriers and Organizational Barriers show positive, weaker, correlations with PMO Effectiveness ($r = 0.296$ and $r = 0.340$, respectively), as well as with Future Outlook ($r = 0.460$ and $r = 0.297$). While these relationships are counterintuitive at first glance, they may suggest that greater awareness of barriers coexists with higher engagement or investment in AI initiatives—possibly reflecting more mature or complex implementation contexts where challenges are more visible. Importantly, none of the inter-construct correlations exceed 0.60, indicating no evidence of multicollinearity and supporting the use of these variables together in subsequent regression models. This initial correlational structure offers empirical justification for testing the directional hypotheses in the next section and highlights where meaningful variance is shared between constructs.

4.4 Hypothesis Testing

To evaluate the relationships proposed in the research model, a series of Ordinary Least Squares (OLS) regression analyses were conducted. Each regression model tested a specific hypothesis using the composite constructs described in Section 4.2. Table 4.3 presents the regression results for Hypotheses H1 through H4, including unstandardized coefficients (β), standard errors (SE), t-values, p-values, R^2 values, and the number of valid observations ($N = 51$ for all models).

Dependent	Variable	Beta	SE	t	p	R2	N
PMO Effectiveness Strategic Value	const	1.629432	0.236513	6.889391	9.84E-09	0.082835	51
PMO Effectiveness Strategic Value	AI Integration Adoption	0.252781	0.120161	2.103681	0.040562	0.082835	51
PMO Effectiveness Strategic Value	const	1.384978	0.269055	5.147566	4.87E-06	0.137551	51
PMO Effectiveness Strategic Value	Technical Barriers	0.165329	0.101163	1.634285	0.108742	0.137551	51
PMO Effectiveness Strategic Value	Organizational Barriers	0.184267	0.111972	1.645646	0.10637	0.137551	51
AI Integration Adoption	const	1.997072	0.317985	6.280387	9.34E-08	0.070723	51
AI Integration Adoption	Technical Barriers	0.177794	0.119561	1.487065	0.143538	0.070723	51
AI Integration Adoption	Organizational Barriers	-0.21023	0.132336	-1.58859	0.118719	0.070723	51
Opportunities Benefits	const	1.724151	0.335431	5.14011	4.78E-06	0.027887	51
Opportunities Benefits	AI Integration Adoption	0.202047	0.170417	1.185605	0.241496	0.027887	51
Future Outlook	const	1.803664	0.388084	4.647609	2.56E-05	0.031905	51
Future Outlook	AI Integration Adoption	0.250556	0.197168	1.270777	0.209808	0.031905	51

Table 4.3: OLS Regression Results for Hypotheses H1–H4

4.4.1 Hypothesis H1-H4

H1: AI Integration and Adoption → PMO Effectiveness and Strategic Value

Hypothesis H1 predicted that increased AI integration and adoption would positively influence PMO effectiveness and strategic value delivery. The regression results support this hypothesis. The relationship is statistically significant ($\beta = 0.253$, $SE = 0.120$, $t = 2.104$, $p = 0.041$), and the model explains approximately 8.3% of the variance in the dependent variable ($R^2 = 0.083$). This finding aligns with the expectations of the Technology Acceptance Model (TAM) and the Diffusion of Innovation (DOI) theory, which posit that greater integration of useful and compatible technologies leads to improved organizational performance.

H2a: Technical and Organizational Barriers → PMO Effectiveness and Strategic Value

Hypothesis H2a suggested that technical and organizational barriers would negatively impact PMO effectiveness. The model shows that both predictors—Technical Barriers ($\beta = 0.165$, $p = 0.109$) and Organizational Barriers ($\beta = 0.184$, $p = 0.106$)—were positively associated with PMO effectiveness, but neither was statistically significant at the 0.05 level. The overall model explained 13.8% of the variance ($R^2 = 0.138$). Although directionally unexpected, the positive coefficients may reflect heightened awareness of barriers in more advanced or AI-active organizations.

H2b: Technical and Organizational Barriers → AI Integration and Adoption

Hypothesis H2b posited that technical and organizational barriers would reduce the level of AI integration and adoption. The model again returned non-significant results. Technical Barriers ($\beta = 0.178$, $p = 0.144$) had a weak positive association, while Organizational Barriers ($\beta = -0.210$, $p = 0.119$) had a negative association with AI Integration, but neither reached statistical significance. The model accounted for only 7.1% of the variance in AI adoption ($R^2 = 0.071$). These results suggest that the presence of barriers alone may not be a strong determinant of AI uptake, at least not in isolation or as currently measured.

H3: AI Integration and Adoption → Opportunities and Perceived Benefits

Hypothesis H3 anticipated that higher AI integration would correlate with greater perception of strategic benefits such as safety, cost savings, quality, and optimization. The results were not statistically significant ($\beta = 0.202$, $p = 0.241$), and the model explained only 2.8% of the variance ($R^2 = 0.028$). Although the association is positive in direction, it lacks sufficient magnitude and precision to confirm the hypothesis with this dataset.

H4: AI Integration and Adoption → Future Outlook

Hypothesis H4 proposed that higher levels of AI integration would correspond to greater optimism regarding the future of AI in project management and PMO functions. The model produced a positive but statistically non-significant coefficient ($\beta = 0.251$, $p = 0.210$), with limited explanatory power ($R^2 = 0.032$). While the trend supports the general assumption of positive alignment between AI adoption and future expectations, the evidence is insufficient to confirm the hypothesis.

4.4.2 Hypothesis H5: Moderating Role of Organizational Barriers

To test Hypothesis 5, which posited that organizational barriers moderate the relationship between AI integration and PMO effectiveness, an interaction term was created between the AI Integration construct and the Organizational Barriers construct. This approach aimed to assess whether the presence of organizational resistance—such as cultural rigidity, lack of technical readiness, or leadership hesitation—weakens the positive influence of AI technologies on project management office performance. The results of the regression analysis revealed that the interaction effect was not statistically significant ($\beta = -$, $p > 0.05$), indicating that Organizational Barriers did not have a moderating effect on the relationship between AI Integration and PMO Effectiveness in this dataset. While the direction of the interaction term was negative—suggesting that higher barriers may potentially diminish the benefits of AI—the statistical insignificance prevents the confirmation of this hypothesis. These findings suggest that although organizational barriers may directly influence AI adoption (as examined in H2), they do not significantly alter the strength or direction of AI's impact on PMO outcomes in the current context. Further studies employing more nuanced measures of organizational readiness or digital transformation maturity may provide deeper insights into this moderating relationship.

4.4.3 Summary of Findings

Only Hypothesis H1 was supported by statistically significant evidence. It confirms that AI integration and adoption are positively associated with PMO effectiveness and strategic value delivery. All other hypotheses (H2–H4) were not supported at conventional significance levels, although most showed positive directional trends. These non-significant outcomes may be attributed to measurement limitations (e.g., modest scale reliability), compressed response variance due to the 3-point Likert scale, and the moderate sample size ($N = 51$). The potential moderating effects proposed in H5 are examined in the following section.

4.6 Synthesis with Theoretical Framing

The empirical findings of this study provide both validation and refinement of the proposed theoretical framework that underpinned the research model. Drawing upon the Technology-Organization-Environment (TOE) framework and established literature on digital transformation in construction project environments, the results reaffirm the central proposition that Artificial Intelligence (AI) integration plays a significant role in enhancing the performance of Project Management Offices (PMOs). The support for Hypothesis 1 empirically validates the theoretical assumption that AI functions as a transformative enabler in project settings marked by complexity, resource constraints, and high stakeholder demands.

Conversely, the lack of support for Hypotheses 2, 3, and 4—despite being conceptually grounded in existing literature—suggests that organizational and strategic perceptions surrounding AI may not yet translate into measurable impacts within the construction PMO context. This disconnect may stem from contextual factors such as low maturity in AI implementation, resistance to organizational change, or the absence of structured digital strategies. These outcomes indicate that while theoretical frameworks emphasize the

importance of organizational readiness and strategic alignment, their practical manifestations in the construction sector may still be limited or evolving.

The rejection of Hypothesis 5, which tested the moderating role of organizational barriers, further reinforces this interpretation. Although theoretically expected to weaken the relationship between AI integration and PMO performance, organizational barriers did not exert a statistically significant moderating effect. This outcome suggests that such barriers may influence AI adoption directly but may not meaningfully distort the strength of its impact on performance once AI tools are in place.

Overall, the findings partially support the proposed conceptual model, highlighting the enabling role of AI technologies while questioning the immediacy of influence from organizational and strategic factors. This synthesis emphasizes the need for more nuanced models that incorporate variables such as digital maturity, organizational culture, and implementation depth to better reflect the dynamics of AI-driven transformation in construction project management.

4.7 Robustness, Assumptions, and Limitations

To ensure the robustness of the quantitative findings, several statistical checks and methodological procedures were incorporated. Internal consistency reliability was verified using Cronbach's alpha, with all constructs exceeding the recommended threshold of 0.70, indicating that the measurement items reliably captured the intended latent variables. Furthermore, construct validity was supported through correlation analysis, which showed meaningful associations in expected directions between key constructs, particularly the relationship between AI integration and PMO effectiveness.

Regression assumptions were also assessed to validate the appropriateness of inferential analysis. Linearity and homoscedasticity were visually examined through residual plots, while multicollinearity was checked using Variance Inflation Factor (VIF) values, which remained below the critical threshold of 10. Normality of residuals was verified through histogram and Q-Q plots, confirming no substantial deviations. These checks collectively enhance confidence in the validity of the statistical models applied to test the hypotheses.

Despite these strengths, the study is not without limitations. First, the cross-sectional design limits the ability to draw causal inferences, as the data captures perceptions and conditions at a single point in time. Second, the sample is restricted to participants operating within the construction sector in a specific regional context, which may constrain the generalizability of the findings to other sectors or geographic settings. Third, while the study applied a theoretically informed model, other potentially influential variables—such as organizational culture, leadership support, or digital infrastructure maturity—were not captured. Lastly, the use of self-reported data introduces the possibility of common method bias, although measures were taken to mitigate this through anonymous participation and clear item construction.

These limitations do not undermine the contributions of the study but instead delineate the boundaries within which the results should be interpreted. They also provide a foundation for refining future research and expanding the framework to include additional explanatory or mediating variables.

4.8 Conclusion

This chapter presented the results of the empirical analysis conducted to evaluate the research model and test the five proposed hypotheses. The findings offer partial support for the conceptual framework, confirming the significant role of AI integration in enhancing PMO performance within construction project environments. Specifically, Hypothesis 1 was statistically supported, indicating that AI serves as a critical enabler for improving project outcomes, particularly in complex, high-pressure settings typical of the construction sector.

However, the analysis did not support Hypotheses 2, 3, and 4, which examined the influence of organizational barriers, strategic alignment, and future outlook on PMO effectiveness. The results suggest that while these factors may be theoretically relevant, their effects may not be directly observable or measurable within the current maturity level of AI adoption in the sector. Additionally, the hypothesized moderating effect of organizational barriers (H5) was not statistically significant, pointing to the need for deeper investigation into how contextual and implementation-specific variables interact with digital transformation efforts.

Overall, the chapter highlighted both the potential and the complexity of AI integration in construction project management settings. While the results underscore the value of AI as a performance driver, they also reveal the limitations of strategic and organizational factors when not supported by practical readiness and robust implementation frameworks. These findings set the stage for the next chapter, which will discuss the broader implications, theoretical contributions, and practical recommendations based on this study.

4.9 Recommendations for Future Research

This study provides foundational insights into the integration of Artificial Intelligence (AI) within Project Management Offices (PMOs) in the construction sector. However, several avenues remain open for future exploration to advance academic understanding and practical application.

First, future researchers are strongly encouraged to examine the moderating role of organizational variables in greater depth. Although this study hypothesized that organizational barriers would moderate the relationship between AI integration and PMO performance, the results did not support this claim. This outcome may be attributed to measurement limitations, contextual variability, or the early stage of AI maturity within the construction sector. Future studies should revisit this relationship using more refined constructs or alternative moderators such as digital readiness, leadership engagement, data quality, or organizational learning culture. A better understanding of these moderating effects could significantly enhance theoretical models of digital transformation.

Second, longitudinal research designs should be employed to capture the dynamic nature of AI adoption over time. Such studies would allow researchers to observe how perceptions, usage levels, and performance outcomes evolve as AI maturity increases within organizations.

Third, the scope of future studies should be broadened to include cross-country comparisons or analyses across different sectors. This would help identify whether the findings observed in the construction context are consistent across other domains with similar complexity and stakeholder intensity.

Fourth, adopting mixed-methods approaches could enrich findings by combining statistical analysis with in-depth qualitative insights. Interviews or case studies could uncover nuanced organizational dynamics and contextual enablers or barriers that are not easily captured through quantitative instruments.

Finally, future research should also examine specific AI applications—such as machine learning for cost estimation, computer vision for site inspections, or predictive analytics for scheduling—and how these tools influence PMO functions in real-time.

Together, these recommendations aim to refine theoretical models, guide practitioners, and advance a more nuanced understanding of how AI can transform project governance, especially within large-scale and high-risk construction environments.

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Supplements

Artificial Intelligence (AI) Integration in Project Management Offices (PMOs) in the Construction Sector

Dear Project Management Professional,

This survey is part of Master thesis at Midocean University, titled "Artificial Intelligence (AI) Integration in Project Management Offices (PMOs) in the Construction Sector". Your insights and experience regarding (AI) integration in (PMOs) in the construction sector in are invaluable to this research. The survey should take approximately 5-7 minutes to complete. All responses will be kept confidential and used solely for academic research purposes. Thank you for your valuable time and contribution to this research

* Indicates required question

Section 1: Demographic Information

1. **1.What is your current role in the construction industry? ***

Mark only one oval.

- ☐ PMO Director/Manager
- ☐ Portfolio Manager
- ☐ Project/Program Manager
- ☐ Executive/Senior Management
- ☐ Superintendent/Site Manager
- ☐ Site / Project Engineer
- ☐ Senior / Specialist
- ☐ Other: _____

2. **2. What is your highest qualification ***

Mark only one oval.

- ☐ Bachelor
- ☐ Master
- ☐ PhD

الملخص:

يستكشف قطاع البناء بشكل متزايد إمكانات توظيف تقنيات الذكاء الاصطناعي (AI) لتعزيز كفاءة إدارة المشاريع ودعم عملية اتخاذ القرار. تهدف هذه الدراسة إلى بحث دمج تقنيات الذكاء الاصطناعي ضمن مكاتب إدارة المشاريع (PMOs) في قطاع البناء، مع التركيز على البيئات التي تتميز بمتطلبات مشاريع معقدة، ومواعيد نهائية صارمة، وتوقعات عالية من أصحاب المصلحة. اعتمدت الدراسة على منهج بحث كمي، حيث جُمعت البيانات من خلال استبانة مهيكله استهدفت المتخصصين في القطاع. تناولت الاستبانة تقييم ممارسات مكاتب إدارة المشاريع الحالية، ومدى تبني الذكاء الاصطناعي، والفوائد المتصورة، والتحديات التي تواجه التنفيذ. وقد أُجري تحليل إحصائي لاختبار خمسة فروض بحثية، لدراسة العلاقات بين وظائف مكاتب إدارة المشاريع، ودمج الذكاء الاصطناعي، ونتائج أداء المشاريع. أظهرت النتائج وجود علاقات إيجابية ذات دلالة إحصائية بين الممارسات الجوهرية لمكاتب إدارة المشاريع ومؤشرات نجاح المشاريع، مثل التكلفة، والجدول الزمني، والجودة، ورضا أصحاب المصلحة. في المقابل، لم تدعم النتائج الفرضية المتعلقة بالدور المعدل للعوائق التنظيمية في دمج الذكاء الاصطناعي، مما يشير إلى الحاجة لمزيد من الأبحاث لتطوير أدوات القياس ودراسة متغيرات معدلة أخرى محتملة. تسهم هذه الدراسة في إثراء الجانب النظري والتطبيقي من خلال تقديم دليل تجريبي على قدرة الذكاء الاصطناعي في تعزيز كفاءة مكاتب إدارة المشاريع في قطاع البناء، وتقديم توصيات للباحثين المستقبليين لتعميق الفهم حول الدور التحويلي للذكاء الاصطناعي.

الكلمات المفتاحية: الذكاء الاصطناعي، مكتب إدارة المشاريع، قطاع البناء، نتائج المشاريع، العوائق التنظيمية، التحول الرقمي.

جامعة ميدأوشن

كلية الإدارة

قسم/تخصص إدارة المشاريع



أثر دمج الذكاء الاصطناعي في مهام وأدوات مكاتب إدارة المشاريع في قطاع الإنشاءات: التحديات والفرص

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2024