



Midocean University

Ph.D. program

**Factors Influencing AI-Based Project Management and Its
Outcomes in Industrial Engineering Firms**

**A Mixed Methods Study of Design and Consultancy
Engineering Projects in Saudi Arabia**

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شركات الهندسة الصناعية
دراسة باستخدام المنهج المختلط لمشاريع التصميم والاستشارات الهندسية في المملكة
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المستخلص

تتناول هذه الدراسة العوامل المؤثرة على إدارة المشاريع القائمة على الذكاء الاصطناعي ونتائجها في شركات الهندسة الصناعية دراسة باستخدام المنهج المختلط لمشاريع التصميم والاستشارات الهندسية في المملكة العربية السعودية. وتتبع مشكلة الدراسة من الأهمية المتزايدة للذكاء الاصطناعي في إدارة المشاريع، والحاجة إلى فهم العوامل التنظيمية والتقنية والبشرية التي تؤثر في تبنيه وفاعليته على أرض الواقع. اتبعت الدراسة المنهج المختلط في إطار تصميم التثليث المتزامن لتعزيز شمولية الفهم ودقة التفسير. وتضمنت المرحلة الكمية استبانة منظمة وُزعت على 250 من المستجيبين المحتملين، وقد استجاب لها فعليًا 103 مشاركين وتم تحليل إجاباته، بينما تضمنت المرحلة النوعية 10 مقابلات شبه مقننة مع ممارسين ذوي خبرة. ودرست الدراسة ستة متغيرات مستقلة هي: خصوصية البيانات وأمنها، مقاومة التغيير، تكلفة تطبيق الذكاء الاصطناعي، التوافق مع البنية التحتية القائمة، تطوير القوى العاملة، والاعتبارات الأخلاقية. كما اعتُبرت إدارة المشاريع المعتمدة على الذكاء الاصطناعي متغيرًا بسيطًا، في حين جرى قياس سبعة مخرجات لمشاريع الإدارة بوصفها متغيرات تابعة. وأظهرت النتائج أن توافق البنية التحتية وتطوير القوى العاملة هما أقوى المتنبئات بتبني إدارة المشاريع المعتمدة على الذكاء الاصطناعي، كما تبين أن هذه الإدارة تؤثر إيجابًا وبصورة معنوية في جميع مخرجات المشاريع. وأكد تحليل الوساطة أن إدارة المشاريع المعتمدة على الذكاء الاصطناعي تمثل آلية رئيسة في تحويل الجاهزية التنظيمية إلى أداء مشروع أفضل. وتتمثل الدلالات العملية للنتائج في أهمية تركيز شركات الهندسة على الاستثمار في البنية التحتية، وتنمية المهارات، والتخطيط الاستراتيجي للتنفيذ.

إقرار

أقر بأن هذه الرسالة هي عملي الأصلي ولم تُقدّم، كليًا أو جزئيًا، للحصول على أي درجة علمية أو مؤهل في أي جامعة أو مؤسسة أخرى. كما أن جميع المصادر والمراجع المستخدمة في هذه الرسالة قد تم الإشارة إليها والاعتراف بها بشكل صحيح. وأقر أيضًا بأن البحث والتحليل والكتابة المقدمة في هذه الرسالة قد أجريتها بنفسني، إلا في الحالات التي تم فيها الاستعانة بمساهمات محددة من الآخرين مع الإشارة إليها بالشكل المناسب.

﴿وَمَا أُوتِيتُمْ مِنَ الْعِلْمِ إِلَّا قَلِيلًا﴾

الشكر والتقدير

أتقدم بأسمى آيات الامتنان والتقدير لكل من ساندني ووقف بجانبني طوال هذه الرحلة.

عائلتي:

أعبر عن خالص تقديري لوالديّ، وزوجتي، وابني، وبناتي، ولكافة أفراد عائلتي على دعمهم المعنوي المستمر، وتشجيعهم، وصبرهم.

الجامعة:

أقدم خالص شكري لمشرفتي، الدكتورة دعاء، ولجنة التقييم على توجيهاتهم القيمة، وملاحظاتهم البناءة، ودعمهم المتواصل.

شكر خاص:

أود أن أتقدم بالشكر الخاص للدكتورة هبة كمال القصبي عطا الله على دعمها ومساهمتها القيمة خلال هذه الرحلة.

الزملاء:

كما أتقدم بالشكر لزملائي الذين ساهموا من خلال المراجعات، والمشاركة في الاستبيان، والمقابلات.

أخيراً، أشكر كل من ساهم، بشكل مباشر أو غير مباشر، في إتمام هذا العمل.

الإهداء

بسم الله الرحمن الرحيم

أهدي هذا العمل إلى والديّ الحبيبين، جزاهما الله خيرًا على دعائهما وإرشادهما ودعمهما اللامحدود.

إلى زوجتي وأطفالي، جزاهم الله خيرًا على صبرهم المستمر.

نسأل الله أن يجزيهم جميعًا خير الجزاء في الدنيا والآخرة.

Abstract

This study investigates the factors influencing the utilization of AI-based project management and its outcomes in design and consultancy engineering firms in Saudi Arabia. The research problem stems from the growing importance of artificial intelligence in project management and the need to understand the organizational, technical, and human factors that affect its utilization and effectiveness in practice. A mixed-methods concurrent triangulation design was used to achieve a comprehensive understanding of the phenomenon. The quantitative phase involved a structured questionnaire distributed to 250 potential respondents, of whom 103 completed and returned the survey, while the qualitative phase included 10 semi-structured interviews with experienced practitioners. The study examined six independent variables: data privacy and security, resistance to change, cost of AI implementation, compatibility with existing infrastructure, workforce development, and ethical considerations. AI-based project management was treated as the mediating variable, and seven project management outcomes were assessed as dependent variables. The results showed that infrastructure compatibility and workforce development were the strongest predictors of AI-based project management utilization, while AI-based project management itself had a significant positive effect on all project outcomes. The mediation analysis confirmed that AI-based project management plays a central role in translating organizational readiness into improved project performance. The findings have practical implications for engineering firms seeking to strengthen AI utilization through targeted investment in infrastructure, skills development, and strategic implementation planning.

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List of Shortcuts:

AI	Artificial Intelligence
AI-PM	AI-based Project Management
ANN	Artificial Neural Network
AVE	Average Variance Extracted
CEO	Chief Executive Officer
CV	Computer Vision
DL	Deep Learning
LLMs	Large Language Models
ML	Machine Learning
NLP	Natural Language Processing
NSDAI	National Strategy for Data and Artificial Intelligence
PMBOK	Project Management Body Of Knowledge
PMO	Project Management Office
PMI	Project Management Institute
PMIS	Project Management Information System
ROI	Return on Investment
RL	Reinforcement Learning
SDAIA	Saudi Data and Artificial Intelligence Authority
SEM	Structural Equation Modeling
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
RMSEA	Root Mean Square Error of Approximation

SRMR	Standardized Root Mean Square Residual
SDKs	Software Development Kits
API	Application Programming Interface
PDPL	Personal Data Protection Law (Saudi Arabia's data privacy regulation)

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Note;

All tables in this thesis (Tables 1–80) were created by the researcher using original data analysis from the study's quantitative survey (n=103) and qualitative interviews (n=10).

CHAPTER 1

1 Introduction and Theoretical Framework:

Given the speed at which science and technology are developing in domains such as manufacturing, engineering, and medicine, project managers increasingly need to use artificial intelligence (AI) technologies to improve productivity. Project management is a strategic competency that applies knowledge, skills, tools, and techniques to meet project requirements. As described by the Project Management Institute (PMI, 2021) in the Project Management Body of Knowledge (PMBOK®) Guide, project management is structured around five key process groups: initiating, planning, executing, monitoring and controlling, and closing. These process groups help ensure that projects are aligned with organizational goals, delivered on time and within budget, and meet or exceed stakeholder expectations. Furthermore, project management encompasses ten knowledge areas: integration, scope, schedule, cost, quality, resource, communication, risk, procurement, and stakeholder management. Together, these areas equip project managers with the competencies needed to navigate complex projects and achieve strategic success.

AI has emerged as a crucial component of design and consultancy engineering projects, particularly in critical domains such as risk assessment, data collection, enhanced data insight and analysis, and improved decision-making. Weng (2023) highlights AI's role in optimizing resource allocation and automating tasks, enabling project managers to focus on strategic objectives while minimizing human error. In the context of Saudi Arabia's Vision 2030, AI emerges as a foundational pillar for achieving the vision's ambitious goals. AI can help forecast the potential effects of resource allocation, notify project managers of impending problems, support project prioritization, and provide information that assists project managers in making decisions aligned with overall project progress. These applications are consistent with the project-management applications discussed by Caniels and Bakens (2011). Utilizing AI tools demonstrates considerable potential across diverse industries. For example, the finance and banking sectors have implemented AI to automate repetitive tasks and process large numbers of transactions with fewer manual errors. El-Khatib and Al Falasi (2021) documented a case study at Mashreq Bank in which AI automation facilitated more than 150,000 transactions in a single day. The authors associated this application with increased productivity, reduced errors, and the generation of more reliable data for decision-making and future projections.

AI applications in project management are also receiving increasing scholarly attention. Taboada et al. (2023) observed that almost half of the selected studies focused on construction project management, while approximately 22% addressed AI use in IT projects. The authors also noted

that AI applications in other sectors, such as healthcare, remained limited, whereas AI-enabled approaches to general project management were comparatively notable.

Building on this discussion, it is evident that AI offers significant potential to enhance project management practices in design and consultancy engineering projects. It provides substantial benefits to both projects and project managers, addressing operational inefficiencies and decision-making challenges. This study aims to explore the application of AI in this domain, addressing existing gaps while raising awareness among project managers and organizations about effectively leveraging AI tools.

This research explores the factors influencing AI utilization in project management and its impact on project outcomes. The following sections provide a structured discussion, beginning with the definition of key terms, research problem, case study, research questions and objectives, followed by the theoretical framework, literature review, methodology, and data analysis.

1.1 Research Problem

The use of AI in project management continues to face challenges related to the design, standardization, and practical implementation of AI tools. Although AI offers considerable potential, its adoption in project management has been relatively slow. Ruiz et al. (2020) attribute this primarily to limited private-sector investment, noting that most AI-related development has instead come from universities and public research institutions. The application of AI tools also remains uneven across project-management areas; Bento et al. (2022) similarly observe that despite AI's broad presence across many industries, its adoption within project management specifically remains uneven, with the underlying reasons unclear but likely tied to persistent uncertainty about how AI can be effectively applied across different project management functions. These challenges are compounded by the limited availability of research and primary data: El-Khatib and Al Falasi (2021), for instance, found relatively few regional research papers addressing AI's impact on project management information systems, and were only able to recruit about half of their intended sample of twenty-five IT and project managers for interviews. Consequently, the field continues to face difficulty in translating theoretical advances into actionable and scalable organizational implementations (Taboada et al., 2023).

To further examine this gap, the present study reviewed prior research on the development of AI in project management and the challenges and opportunities associated with its practical application. Previous studies suggest that AI adoption in project management has developed more slowly than project-management activity in general (Davahli, 2020; Munir, 2019). This slower adoption may help explain why project-intensive industries, including manufacturing and construction, have been identified as AI laggards (Blanco et al., 2018). At the same time, the increasing volume of project-management data may create further opportunities for AI applications (Ong & Uddin, 2020; Kuster, 2021).

Other studies have questioned whether the potential of AI has been fully realized across all project-management knowledge areas (Pereira et al., 2021, 2022, as cited in Bento et al., 2022). Research has also continued to examine the conditions associated with project success and the expected future influence of AI on project-management practice (Ruiz et al., 2020; Fridgeirsson et al., 2021). Collectively, these findings reinforce the need for empirical research examining how organizational factors influence AI-PM utilization and how AI-PM affects project outcomes in design and consultancy engineering projects.

Wrobel et al. (2025) identified gaps in existing AI-project frameworks and emphasized the need for guidance that addresses the economic, ethical, organizational, and practical demands of AI projects. Hassi (2024), drawing on Merilehto (2018), explained that current AI technologies are generally task-specific and can support project workflows through activities such as scheduling, resource allocation, progress tracking, and the analysis of patterns that may indicate potential delays or risks. Although prior research presents varied perspectives, there is consistent agreement that the practical utilization of AI tools in project management remains limited. This gap motivates the present study to investigate the factors influencing AI-PM utilization and its relationship with project outcomes in design and consultancy engineering projects. El-Khatib and Al Falasi (2021) argued that AI would become an integral part of organizational strategy in the future.

Exploratory/ Practitioners Insights:

Based on the researcher's own experience in project management within Saudi design and consultancy engineering firms, and informal discussions with a small number of senior practitioners (including project directors, project managers, and CEOs), the researcher formed preliminary impressions that the research problem is not only theoretical but clearly present in practice. These reflections were not collected through a formal exploratory study and should not be interpreted as empirical evidence. They are offered only as motivating context to illustrate how AI is currently being used and perceived in real projects. Together with the structured literature review, these informal observations highlighted several recurring themes: many practitioners noted the absence of practical AI tools for project management in their organizations; a smaller number described incomplete attempts to use AI tools, hindered by challenges such as incompatibility with existing infrastructure, insufficient training, and lack of managerial support; and some acknowledged the use of AI-supported tools, although their application was primarily limited to automating routine tasks.

While these practitioner observations and informal consultations helped to confirm the practical relevance of the problem and illustrate how AI is currently used in real projects, the final identification of the study variables were primarily guided by the structured literature review and theoretical framework presented in sections 1.8 and 2.2, with practitioner insights providing additional practical validation.

As a project management practitioner in Saudi Arabia, the researcher also observed a lack of advanced AI tools beyond basic automation. However, it is possible that some AI tools are being used in organizations but are not publicly documented. This study, therefore, aims to identify the

challenges and opportunities influencing the use of AI in design and consultancy engineering project management.

For example, retrieving historical data for future projects such as risk identification, cost estimation, or quality records often requires significant time and effort due to the lack of AI-powered tools, whereas organizations with AI tools can retrieve such data more quickly and efficiently. However, concerns about data privacy and security deter organizations from utilizing AI, as they are reluctant to expose sensitive information externally (Alshaikhi & Khayyat, 2021; Kuster, 2021).

A related challenge concerns data analysis: human analysts require considerable time to process large volumes of complex data, whereas AI-powered tools can analyze such datasets far more quickly, offering faster and more actionable insights (Korke et al., 2023; Sahadevan, 2023).

AI utilization also comes with substantial costs. Organizations must upgrade infrastructure to ensure compatibility with AI technologies and incur ongoing expenses for training and maintenance, a burden further compounded by the limited availability of skilled professionals with AI expertise (Bughin et al., 2018; Weng, 2023).

Ethical and social challenges further hinder utilization. Resistance to change often arises from employees' reluctance to leave familiar practices, with fear of job displacement compounding this resistance, making change-management strategies critical to reassuring employees while maintaining operational efficiency (Bodea et al., 2020; Bharati & Sandbrink, 2024).

These difficulties highlight the necessity of integrating AI into project management in a thorough and calculated manner, guaranteeing that its advantages are seen while resolving the related obstacles. Building on this discussion and addressing the identified research gap, this study seeks to answer the following major questions Q1, Q2 & Q3:

1.2 Research Questions

Major Research Question 1:

(Factors Influencing the Utilization of AI-Based Project Management- Independent Variables)

Q1: What factors influence the utilization of AI-based project management in design and consultancy engineering projects?

Major Research Question 2:

(AI's Impact on Project Outcomes - Dependent Variables)

Q2: What are the outcomes of AI-based project management in design and consultancy engineering projects?

Major Research Question 3:

(Mediating Role of AI in Project Management)

Q3: How does AI-based project management mediate the relationship between influencing factors and project outcomes?

Hence, each of the above major questions are broken down to subsequent questions as below;

Major Research Question 1: Factors Influencing AI Use in Project Management (Independent Variables & Corresponding Research Questions)

Q1: What factors influence the utilization of AI tools in project management for design and consultancy engineering projects?

1. Data Privacy and Security
Q1A: How do concerns around data privacy and security influence AI utilization?
2. Resistance to Change
Q1B: How does resistance to change influence AI tool utilization?
3. Cost of AI Implementation
Q1C: How does the cost of AI implementation influence AI tool utilization?
4. Compatibility with Existing Infrastructure
Q1D: How does infrastructure compatibility influence AI tool utilization?
5. Workforce Development
Q1E: How do workforce development and training influence AI tool utilization?
6. Ethical Considerations
Q1F: How do ethical considerations influence the utilization of AI in project management?

Major Research Question 2: AI's Impact on Project Outcomes (Dependent Variables & Corresponding Research Questions)

Q2: What are the outcomes of AI-based project management in design and consultancy engineering projects?

1. Decision-Making
Q2A: How does AI-based project management influence decision-making?
2. Project Quality
Q2B: How does AI-based project management influence overall project quality?
3. Data Collection Accuracy
Q2C: How does AI-based project management influence data collection accuracy?
4. Data Analysis
Q2D: How does AI-based project management influence data analysis capabilities?

5. Risk Identification Accuracy

Q2E: How does AI-based project management influence risk identification accuracy?

6. Time Saving

Q2F: How does AI-based project management influence time-saving for project managers?

7. Communication

Q2G: How does AI-based project management influence communication?

Major Research Question 3: Role of AI-Based Project Management as a Mediating Variable

Q3A: How does the utilization of AI-based project management influence the long-term sustainability of organizations managing design and consultancy engineering projects?

1.3 Research Importance

1.3.1 Scientific Importance:

This study distinguishes itself by focusing on identifying and measuring the factors influencing project management through the utilization of AI. By addressing the scarcity of research on AI tools in project management, it fills a critical gap in the academic literature, particularly in the context of design and consultancy engineering projects. The limited availability of studies in this area, as highlighted by several researchers, underscores the importance of conducting such focused investigations.

Similarly, many studies have predicted the future evolution of AI in project management. Ruiz et al. (2020), for example, note that "looking to the future 25 years from now, it is likely that there will exist an AI capable of managing the entire project, albeit with some form of human supervision" (p. 61). Despite these predictions, there is little quantitative research examining the moderating impact of AI tools on project management. This study will address this gap by quantifying the effects of applying AI in project management and measuring its impact on key variables. Such an investigation will contribute significantly to understanding the factors that influence project management through AI, specifically in design and consultancy engineering projects.

1.3.2 Practical Importance:

To achieve strategic objectives and enhance project value, companies must prioritize the practical utilization of AI in project management. Leveraging AI has become essential for staying competitive amidst rapidly evolving technologies. Organizations looking to optimize AI's benefits in project management techniques must comprehend the elements that lead to its successful and long-lasting deployment.

Understanding the factors that contribute to the successful and sustainable implementation of AI is critical for organizations seeking to maximize their project outcomes in project management practices. By exploring both challenges and opportunities, this study aims to provide actionable insights that will enable organizations to integrate AI effectively, ensuring its long-term value in design and consultancy engineering projects.

1.4 Research Objectives

This study aims to achieve the following objectives:

1. Identify and evaluate the key factors influencing the utilization of AI tools in project management within design and consultancy engineering projects.
2. Examine how AI-based project management mediates the relationship between influencing factors and project outcomes.
3. Analyze the direct influence of these factors on the outcomes of AI-based project management.
4. Describe the distribution of AI utilization and outcomes across different organizational types, sizes, and participant demographics.
5. Propose actionable recommendations based on empirical findings to enhance AI-based project management practices in the Saudi design and consultancy engineering sector.

1.5 Summary of the chapter

Chapter 1 established the research foundation by articulating the problem of limited AI utilization in Saudi design and consultancy firms despite Vision 2030 priorities, framed through three major research questions on influencing factors, outcomes, and mediation effects. The study defines five objectives, and three major research questions addressed factors influencing AI utilization (RQ1), project management outcomes (RQ2), and AI-based project management mediation (RQ3), supported by proposed 20 testable hypotheses (H1–H4 covering direct, mediated, and outcome paths), and introduced the conceptual model linking six independent variables (privacy, resistance, costs, infrastructure, workforce, ethics) through AI-based PM to seven outcomes (decision-making, quality, data accuracy, analysis, risk Identification, time savings, communication). Table 1 summarizes 61 prior studies identifying gaps such as a limited Saudi/design focus, no integrated mediation models, and insufficient practical recommendations, which this study addresses. The literature commentary highlighted alignments and differences, justifying the need for this empirical mediation analysis. These foundations guide the theoretical development, methodology, and hypothesis testing in subsequent chapters.

CHAPTER 2

2 Theoretical Framework (Related Literature Review)

The theoretical framework is structured into the following sections: an introduction to the theoretical framework and its constituent variables (independent, mediating, and dependent), a review of previous literature, and the study's conceptual model.

2.1 Introductions to the Theoretical Framework

A theoretical framework provides the foundational structure for any research study by incorporating established theories, models, and empirical insights to justify the relationships between key variables. This study explores the factors influencing AI utilization in project management, the mediating role of AI-driven project management practices, and their influence on project outcomes within design and consultancy engineering projects. The research adopts a multi-theory approach to explain AI utilization in project management:

Integrated AI Project Management Framework;

AI has emerged as a transformative tool in project management, reshaping traditional workflows through automation, predictive analytics, and real-time monitoring. The Integrated AI Project Management Framework provides a structural foundation for understanding how AI tools optimize scheduling, resource allocation, and data-driven decision-making in design and consultancy projects (Weng, 2023). By adopting this framework, organizations can ensure seamless AI integration, resulting in improved efficiency, risk management, and project outcomes.

AI-Driven Decision-Making Theory;

Decision-making is a core competency in project management, requiring accurate, timely, and data-driven insights. The AI-Driven Decision-Making Theory supports this study's exploration of how AI enhances risk assessment, scenario analysis, and strategic planning. By leveraging machine learning (ML) algorithms, AI can identify patterns, reduce cognitive biases, and improve forecasting accuracy, allowing project managers to make more informed and proactive decisions (Odejide & Edunjobi, 2024). This theory directly aligns with the study's dependent variable in the model, particularly enhanced decision-making quality and performance, and reinforces the argument that AI utilization leads to smarter, more efficient project execution.

Sustainable AI Utilization Model;

Despite its benefits, AI utilization in project management is often hindered by financial constraints, data security concerns, workforce resistance, and ethical challenges. The Sustainable AI Utilization Model underpins this study's analysis of independent variables that influence utilization, ensuring a structured examination of cost, infrastructure compatibility, and training needs (Alshaikhi & Khayyat, 2021). By applying this model, the study provides insights into how organizations can strategically implement AI, balancing the short-term challenges with long-term benefits. The findings will aid decision-makers in developing AI adoption roadmaps tailored to design and consultancy firms.

Adaptive AI Utilization Theory;

AI implementation is not a one-time solution, organizations must continuously adapt AI tools based on evolving project needs, industry requirements, and technological advancements. The Adaptive AI Utilization Theory aligns with this research by emphasizing the flexibility required for AI utilization in project management (Bento, 2022). This study examines how resistance to change, workforce adaptability, and evolving AI capabilities, highlighting how dynamic organizational responses affect the long-term effectiveness of AI-driven project management strategies.

Collaborative AI Management Paradigm;

The literature on AI in project management points to a wide range of organizational, technical, human, and governance-related conditions that may shape how AI is utilized and what outcomes it produces. The six factors examined in this study were identified through the convergence of three sources: their frequency and prominence across the studies reviewed in this chapter, their alignment with the theoretical frameworks introduced above, particularly the Integrated AI Project Management Framework and the Sustainable AI Utilization Model, and the researcher's own professional observations in Saudi design and consultancy engineering firms, discussed further in Chapter 1. Where these three sources converged, a factor was retained for inclusion in the conceptual model; other conditions discussed in the literature may exist but were not consistently supported across all three sources within the scope of this study. The sections that follow examine each of the six retained factors in more depth, before the full pattern of relationships among them is developed later in this chapter.

2.1.1 Independent Variables:

2.1.1.1 Data Privacy and Security:

Data privacy and security concern the protection, confidentiality, integrity, and controlled use of data collected, stored, and processed by AI systems. Poor data quality and data silos can limit AI effectiveness, while limited understanding of what data are entered into and retained by AI models creates additional privacy and transparency challenges (Alshaikhi & Khayyat, 2021; Kuster,

2021). Because project teams often handle sensitive design, client, financial, and operational information, Weng (2023) cautions that connecting AI tools to project-management platforms creates a data pathway through which such information could reach unauthorized parties if adequate safeguards are not in place.

Data privacy and security are therefore important conditions for AI utilization in design and consultancy engineering projects. Organizations need to work with IT and cybersecurity departments to establish appropriate practices, including access controls, encryption, threat detection, data-quality controls, and clear rules for the use of AI tools. Transparency with stakeholders regarding data use and protection measures is also necessary to strengthen trust (Weng, 2023). In this study, data privacy and security are examined as organizational factors that may influence both the utilization of AI-based project management and project outcomes.

2.1.1.2 Resistance to Change

Resistance to change refers to organizational and employee reluctance to adopt new technologies, modify established work practices, or replace familiar systems. In AI-based project management, resistance may arise from fear of job displacement, limited awareness of AI capabilities, satisfaction with existing practices, insufficient training, and concerns about changing established workflows. Although AI adoption is associated with improved productivity, decision-making, reporting, and time available for strategic activities (Bodea et al., 2020), these potential benefits may not be realized when employees and managers are unwilling or unable to use AI tools effectively.

The rapidly changing nature of AI further increases the need for organizational adaptability and careful implementation planning. Successful integration requires strategic planning, flexibility, appropriate task selection, and awareness of existing infrastructure requirements (Bharati, 2024). Change-management training, AI literacy, data literacy, technical skills, and stakeholder involvement can reduce resistance and support adoption (Bharati & Sandbrink, 2024). Evidence also indicates that insufficient planning and collaboration may delay implementation, particularly when employees are not adequately prepared or informed about the changes (El-Khatib & Al Falasi, 2021; Tubman, 2022).

Accordingly, resistance to change is treated in this study as a factor that may constrain the utilization of AI-based project management and its contribution to project outcomes. A planned adaptation process involving communication, training, stakeholder participation, and continuous monitoring is especially relevant to design and consultancy engineering organizations.

2.1.1.3 Cost of AI Implementation

Cost of AI implementation includes the financial resources required to acquire, integrate, operate, maintain, update, and support AI-based project-management systems. Adoption may be difficult because of software licensing, equipment, infrastructure adaptation, data integration, employee training, change management, maintenance, and technical-support expenses. These costs can be

particularly restrictive for organizations with limited financial resources (Alshaikhi & Khayyat, 2021; Weng, 2023).

Although AI may provide cost-effectiveness, reliability, and support for decision-making, organizations must evaluate its short-term and recurring financial implications. Data integration and workforce development can require substantial resources because organizations may need to consolidate data, adapt existing processes, and develop new employee capabilities. Broader economic pressures may also increase the financial burden of AI adoption and create differences in technological capacity between organizations with greater and fewer resources (Kuster, 2021; Bughin et al., 2018).

Cost is therefore relevant to this study as a potential barrier to AI utilization and as an organizational condition that may affect project outcomes. The study examines whether implementation cost influences the adoption and effective use of AI-based project management in design and consultancy engineering firms.

2.1.1.4 Compatibility with Existing Infrastructure:

Compatibility with existing infrastructure refers to the extent to which AI systems can operate with an organization's current hardware, software, data structures, legacy systems, and operational processes. AI integration may require organizations to modify existing project-management systems, address data-format and interoperability problems, improve scalability, or replace outdated infrastructure. Dependence on older tools and techniques may be inadequate for complex projects that require more advanced data processing and automation (Mahmood et al., 2023).

Infrastructure compatibility is a significant consideration because AI systems depend on reliable data flows and effective connections among organizational platforms. Legacy systems, fragmented data, limited API support, and incompatible formats can delay implementation, increase costs, and create reluctance to adopt AI tools. Organizations may therefore face a choice between adapting existing systems and investing in modern AI-compatible infrastructure (Weng, 2023).

In design and consultancy engineering projects, infrastructure compatibility may affect the continuity of workflows, the reliability of project information, and the scalability of AI applications. It is examined in this study as an influencing factor that may affect both AI-based project management utilization and project outcomes.

2.1.1.5 Workforce Development:

Workforce development refers to the training, education, technical expertise, leadership capability, and continuous professional development required to use and integrate AI-based project-management tools. Without adequate workforce preparation, project managers and team members may lack the skills needed to interpret AI outputs, operate AI systems, integrate them into workflows, and apply their recommendations responsibly (Weng, 2023).

Effective AI utilization requires more than access to technology. It also depends on AI literacy, data literacy, analytical capability, technical proficiency, leadership, and the ability to work with AI-supported decision-making. A shortage of trained technical personnel can hinder AI adoption and prolong implementation, while leadership and interpersonal skills may affect an organization's ability to manage AI-related change (El-Khatib & Al Falasi, 2021; Alshaikhi & Khayyat, 2021). Upskilling is particularly important because AI-based project management requires capabilities that may differ from those used in conventional project-management practices (Belharet, 2020).

Workforce development is therefore treated as a central organizational factor in this study. It may directly influence AI-PM utilization and project outcomes by enabling employees to use AI tools effectively, interpret their outputs, support adoption, and translate AI capabilities into improved project-management practices.

2.1.1.6 Ethical Considerations:

Ethical considerations in AI-based project management include fairness, bias prevention, transparency, explainability, accountability, human oversight, and the responsible handling of data and AI-generated recommendations. These issues are important because AI systems may reproduce biases in training data, generate decisions that are difficult to explain, or produce outcomes that affect project stakeholders without adequate human review (Kuster, 2021; Weng, 2023).

Explainability and interpretability are particularly important when AI-supported decisions may adversely affect individuals or organizations. Ethical governance should therefore address the full AI lifecycle, including data collection, model development, deployment, monitoring, and accountability for errors. Concerns about job displacement and the possible devaluation of human expertise also require organizations to balance AI-supported automation with human judgment and responsible workforce transition (Ong, 2020; Weng, 2023).

In the Saudi context, ethical AI utilization is connected to data governance, privacy protection, regulatory compliance, and stakeholder trust. Ethical considerations are examined in this study as an influencing factor that may shape the acceptance, utilization, and responsible implementation of AI-based project management in design and consultancy engineering projects.

2.1.2 Mediating Variable:

AI-based project management functions as the mediating variable in this study's conceptual model, representing the mechanism through which the influencing factors affect project outcomes (see Hayes, 2018, for a detailed treatment of mediation analysis).

2.1.2.1 Project Management based on Artificial Intelligence:

Project Management based on Artificial Intelligence refers to the use of AI-supported tools and practices to automate processes, analyze project data, identify risks, support decision-making, allocate resources, monitor progress, and improve communication. In this study, AI-based project

management is positioned as the mechanism through which organizational factors may influence project-management outcomes.

AI can address project-management challenges associated with processing large volumes of data, limited human time, rule-based scheduling, and the coordination of project activities (Alshaikhi & Khayyat, 2021). AI applications include process automation, chatbot assistance, machine-learning-based analysis, and more autonomous management functions (Sahadevan, 2022; Al-Ghamdi & Darman, 2022). AI can also support scope management, defect resolution, stakeholder coordination, and proactive risk detection by analysing historical and real-time project information (Sahadevan, 2023; Korke et al., 2023).

Despite these benefits, AI-PM utilization may be constrained by data-security concerns, resistance to change, insufficient training, implementation costs, ethical risks, and excessive reliance on automated recommendations (Weng, 2023). Human judgment therefore remains important, and AI should support rather than replace project-management expertise. In this study, AI-based project management is examined as the mediating variable linking the six influencing factors to the seven project-management outcomes.

2.1.3 Dependent Variables:

The dependent variables in this study are the project-management outcomes hypothesized to be influenced by the six independent variables and by AI-based project management utilization (see Creswell & Plano Clark, 2018, for a general treatment of variable roles in research design).

2.1.3.1 *Enhancing Decision Making:*

Enhancing decision making refers to the ability of project managers and organizations to make faster, more accurate, timely, and evidence-based decisions. AI supports this dimension by processing complex information, identifying patterns, evaluating risks, simulating alternatives, and generating predictive insights.

Project-management information systems can facilitate timely decision-making and contribute to project success, while the integration of AI into these systems can improve monitoring, control, verification, efficiency, and decision accuracy (El-Khatib & Al Falasi, 2021; Raymond & Bergeron, 2008). AI can also identify gradual trends within large data streams that may be difficult to detect through manual analysis (El-Khatib & Al Falasi, 2021).

AI-supported decision-making is relevant to design and consultancy engineering projects because project managers must evaluate cost, schedule, risk, design, and resource information. Applications such as scenario simulation and predictive analysis can support planning and improve responses to complex project conditions (Mahmood et al., 2023). In this study, enhancing decision making is examined as one of the project-management outcomes associated with AI-PM utilization.

2.1.3.2 Enhancing Project Quality:

Enhancing Project Quality refers to the extent to which AI-based project-management practices improve the accuracy, consistency, monitoring, and delivery quality of project outputs. AI may contribute to project quality through automation, predictive analytics, improved documentation, resource optimization, risk assessment, and early identification of errors or performance problems.

AI-supported project-management systems can improve workflow efficiency, scheduling, documentation, cost management, and coordination across project teams (Mahmood et al., 2023). By analysing project information and identifying potential issues earlier, AI may help project managers maintain alignment with project objectives and reduce errors. AI-supported systems may also improve data collection and inspection processes, thereby strengthening the information used for quality control (El-Khatib & Al Falasi, 2021).

This outcome is particularly relevant to design and consultancy engineering projects, where quality depends on accurate documentation, coordinated information, timely reviews, and effective monitoring of project requirements. In this study, Enhancing Project Quality is examined as an outcome of AI-based project-management utilization.

2.1.3.3 Data Collection Accuracy:

Data Collection Accuracy refers to the correctness, consistency, completeness, and reliability of information collected during project-management activities. AI can improve this dimension by automating data capture, validating entries, reducing manual errors, and integrating information from multiple sources.

AI-supported data collection and analysis can help identify patterns that may be difficult to detect manually, while predictive tools can support more accurate estimates of project duration and cost (Tubman, 2022; Mahmood, 2023). Building Information Modeling provides a platform for collecting, sharing, exchanging, and analysing project information in real time, thereby supporting communication, coordination, and data accuracy (Korke et al., 2023).

AI chatbots, sensors, drones, and other automated systems can further reduce manual intervention and support the creation of reliable historical project records (Tubman, 2022; Korke et al., 2023). Computer vision, natural language processing, and machine learning may also improve data processing, security, and productivity (Mahmood, 2023). In this study, Data Collection Accuracy is examined as a project-management outcome associated with AI-PM utilization.

2.1.3.4 Enhancing Data Analysis:

Enhancing Data Analysis refers to the ability to process large and complex project datasets, identify patterns and relationships, generate insights, and support evidence-based project decisions. AI can analyse information at high speed and reveal trends, risks, inefficiencies, and correlations that may be overlooked through conventional methods.

AI-supported systems can connect information from different project subsystems and provide a more comprehensive view of project conditions (Sahadevan, 2023). Machine-learning algorithms can also analyse large datasets and uncover previously unknown information, supporting risk identification, resource allocation, forecasting, and operational improvement (Korke et al., 2023). These capabilities are relevant to design and consultancy engineering projects, which generate complex technical, financial, scheduling, and stakeholder data.

AI-generated analysis should, however, complement rather than replace professional judgment. Project managers need to evaluate AI recommendations in relation to their experience, project context, and professional responsibilities (Weng, 2023). In this study, Enhancing Data Analysis is examined as an outcome through which AI-PM may improve project-management performance.

2.1.3.5 Risk Identification Accuracy:

Risk Identification Accuracy refers to the ability to recognize, assess, and anticipate potential project risks with sufficient timeliness and precision to support preventive action. AI can contribute to this outcome by analysing historical data, issue logs, real-time information, and patterns associated with delays, cost problems, resource constraints, or other project threats.

AI-supported risk identification can help project managers detect emerging risks and develop mitigation strategies earlier. Risk-management processes still depend on human expertise and judgment, but AI can provide systematic analysis and additional evidence to support more informed decisions (Alada, 2023). In project-management and construction contexts, AI methods can imitate aspects of expert knowledge, generate predictive insights, and support early troubleshooting (Korke et al., 2023).

The integration of historical and real-time data, including information collected through sensors and drones, may further improve risk monitoring and reduce reliance on error-prone manual inspections (Tubman, 2022; Korke et al., 2023). AI-based security tools and automated processes can also support the identification of technological and operational threats (Sahadevan, 2023; Weng, 2023). In this study, Risk Identification Accuracy is examined as a project-management outcome of AI-PM utilization in design and consultancy engineering projects.

2.1.3.6 Time Saving (Operation Efficiency):

Time Saving (Operation Efficiency) refers to the reduction of time spent on routine, administrative, and repetitive project-management activities. AI can support this outcome by automating scheduling, data entry, reporting, monitoring, documentation, and other tasks, allowing project managers to devote more time to strategic planning, risk management, stakeholder engagement, and decision-making.

Although AI can automate many daily tasks, project-management professionals continue to provide value through mentoring, communication, judgment, empathy, and stakeholder leadership (Belharet, 2020). AI-supported scheduling, bots, predictive analytics, and automated reporting may reduce administrative workload and enable project managers to focus on higher-value

activities (Khayyat & Alshaikhi, 2021; Belharet, 2020). Advanced analytics can also provide timely insights and support scenario-based planning, helping managers respond more quickly to project changes (Korke et al., 2023).

Time efficiency is therefore an important outcome in design and consultancy engineering projects, where project managers often coordinate substantial volumes of information and routine reporting. In this study, Time Saving (Operation Efficiency) is examined as a project-management outcome associated with AI-PM utilization.

2.1.3.7 Effective Communication:

Effective Communication refers to the timely, accurate, transparent, and coordinated exchange of information among project teams, clients, consultants, contractors, and other stakeholders. AI can support communication by automating documentation, generating reports and meeting summaries, providing real-time updates, translating information, and connecting project participants through shared platforms.

Collaboration in project-based organizations involves information sharing, mutual learning, trust, and coordinated action toward shared objectives (Tubman, 2022). AI-supported platforms and process-mining tools can improve workflow visibility, identify bottlenecks, monitor deviations, and reveal patterns of collaborative behaviour (Korke et al., 2023). AI can also assist with email drafting, reporting, language translation, corrective-action recommendations, and stakeholder communication (Weng, 2023; Sahadevan, 2023).

These capabilities may reduce misunderstandings, improve transparency, support stakeholder participation, and facilitate more timely decisions. However, effective communication still depends on human coordination and professional judgment. In this study, Effective Communication is examined as a project-management outcome associated with AI-PM utilization in design and consultancy engineering projects.

2.2 Research Concepts:

This study investigates the relationships among three groups of variables: factors influencing AI utilization, AI-based project management as the mediating variable, and project-management outcomes associated with AI utilization. Each concept is presented below in two parts: a terminological definition grounded in the literature, and an operational definition describing how the concept is applied and measured within this study.

Terminological Definitions

Influencing Factors. A wide range of organizational, technical, financial, human, and governance-related conditions have been associated with AI adoption in project management. Among the factors most consistently identified in the literature reviewed in Section 2.1 — including data privacy and security, resistance to change, implementation cost, infrastructure compatibility, workforce development, and ethical considerations (e.g., Khayyat & Alshaikhi,

2021; Weng, 2023; Belharet et al., 2020) — this study focuses on those that recurred most prominently and that the researcher's own professional experience suggested as particularly relevant to the Saudi design and consultancy engineering context.

Mediating Variable. AI-based project management refers to the integration and application of artificial intelligence technologies within project-management activities, including workflow automation, decision support, resource optimization, and risk analysis (Weng, 2023). The construct is discussed in detail in Section 2.1.2.

Project Outcomes. The literature associates AI utilization with a range of project-management performance outcomes. This study examines several of the outcomes that appeared most frequently across the reviewed studies, as discussed individually in Section 2.1.3.

Operational Definitions

For the purposes of this study, each construct is operationalized through respondents' self-reported perceptions, collected via structured survey items administered to project management practitioners in Saudi design and consultancy engineering firms. The influencing factors are operationalized as respondents' perceived organizational and technical conditions affecting AI utilization; the mediating variable is operationalized as respondents' reported extent of AI integration into project-management workflows; and project outcomes are operationalized as respondents' perceived changes in project-management performance associated with that integration. The specific measurement items and scales used to operationalize each construct are presented in the instrumentation section of Chapter 3.

2.2.1 Conceptual Model:

The conceptual model (Figure 1) specifies three hypothesized relationships: the influencing factors' effects on AI-based project management utilization, AI-based project management's effects on project outcomes, and the influencing factors' potential direct effects on outcomes independent of AI-based project management.

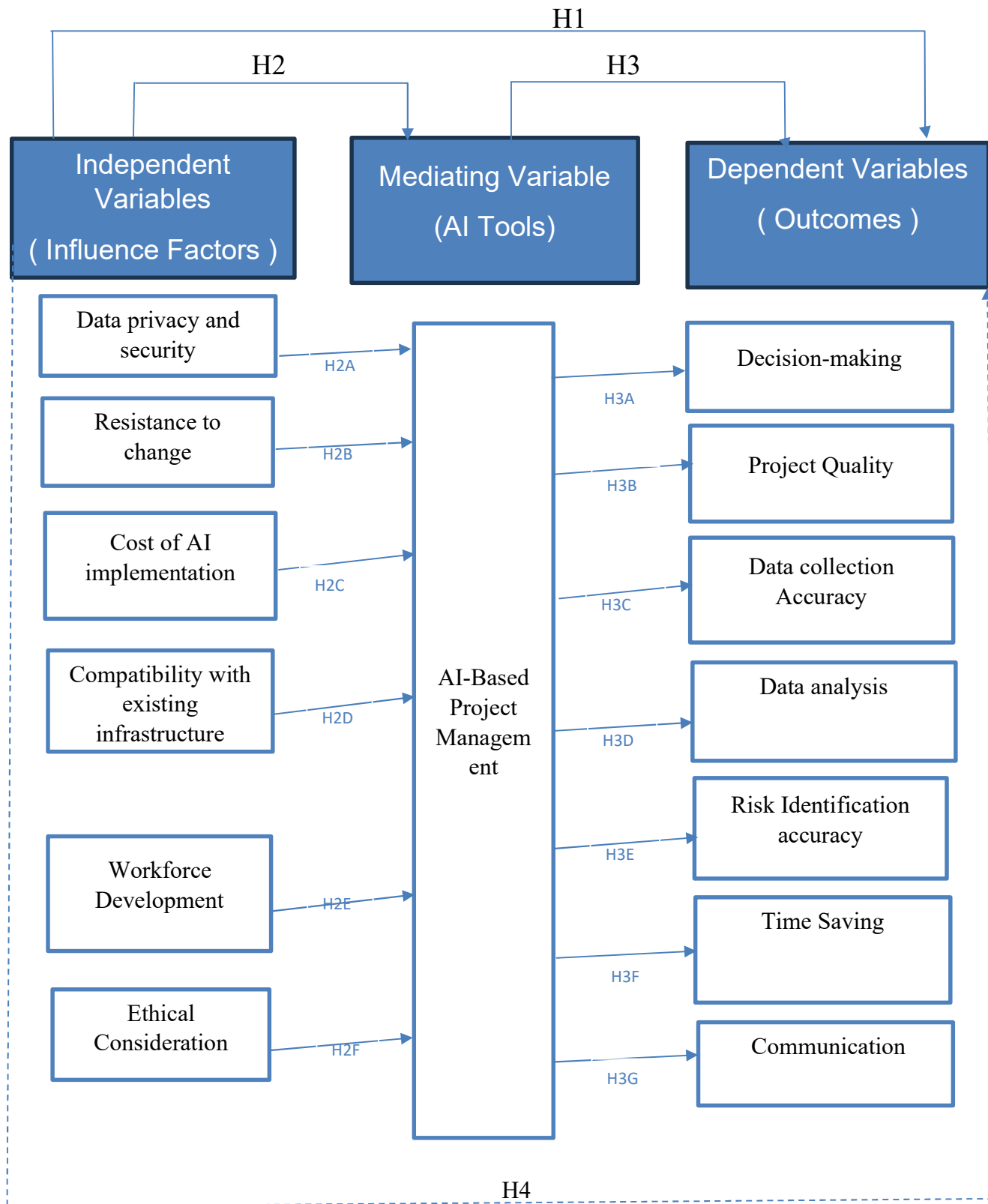


Figure (1) The study conceptual model

The conceptual model provides the basis for empirically testing the proposed relationships among the independent variables, AI-based project management, and the dependent variables. It examines whether the influencing factors directly affect project outcomes, whether they influence the utilization of AI-based project management, and whether AI-based project management mediates their effects on project outcomes.

The model is grounded in the Saudi Arabian context, where Vision 2030 emphasizes technological development and AI utilization as drivers of economic diversification. Accordingly, the framework considers context-specific issues such as data privacy, regulatory compliance, the National Data Governance Framework, and the role of the Saudi Data and Artificial Intelligence Authority (SDAIA). This contextual grounding supports the relevance of the model to design and consultancy engineering projects in Saudi Arabia.

The framework is intended to provide practical insights into the organizational conditions required for effective AI utilization, a structured theoretical basis for examining AI-based project management, and policy-relevant evidence concerning the enablers and barriers to AI adoption in Saudi engineering and consultancy firms.

2.3 Previous Literature Review:

The literature reviews are categorized based on the relationships between the study variables as follows:

2.3.1 Literature Review Focused on the Relationship Between Independent Variables and Dependent Variables

The studies categorized under this section primarily examine and analyze how various factors such as data privacy, cost, change resistance, ethical concerns, and infrastructure compatibility impact AI utilization and ultimately influence project management outcomes.

Several studies (e.g., Waqar et al., 2023; El-Khatib & Al Falasi, 2021; Mahmood et al., 2023; Yaseen et al., 2020) highlight how AI utilization leads to improvements in project scheduling, cost efficiency, and decision-making accuracy. These studies emphasize that when AI utilization is properly managed, it enhances efficiency, risk mitigation, and project success. However, barriers such as data security concerns (Weng, 2023) and high implementation costs (Nagireddy, 2023) create obstacles that limit AI's effectiveness. The research further underscores that AI improves risk prediction (Lishner & Shtub, 2022), optimizes scheduling (Parekh & Mitchell, 2024), and enhances cost estimation accuracy (Elmousalami, 2020). However, infrastructure limitations (Fridgeirsson et al., 2023) and lack of skilled personnel (Sahadevan, 2023) often hinder its full integration into project workflows.

While these studies contribute valuable insights, they often focus on general project management practices (construction, healthcare, and manufacturing) rather than design and consultancy

engineering projects. Moreover, most research does not integrate multiple influencing factors holistically, instead assessing them in isolation.

2.3.2 Literature Review Focused on the Relationship Between Independent Variables and Mediating Variables

These studies investigate how AI utilization barriers such as change resistance (Kelepouris, 2023), data quality concerns (Khayyat & Alshaikhi, 2021), and ethical issues (Kuster, 2021) influence the effectiveness of AI-driven project management.

Many studies (e.g., Weng, 2023; Bento et al., 2022; Bharati & Sandbrink, 2024) highlight that AI's potential is often restricted by organizational resistance and technical barriers. Poor data quality and security risks hinder AI's ability to provide meaningful project insights (Tubman, 2022), while explainability issues (Kuster, 2021) limit trust in AI-based decision-making. Another key barrier is infrastructure compatibility. Korke et al. (2023) and Al-Ghamdi & Darman (2022) discuss how legacy systems often create bottlenecks in AI integration. Similarly, Muller et al. (2024) highlight that inadequate training and lack of skilled professionals further delay AI utilization in project management settings.

Existing research extensively discusses AI utilization barriers but does not fully explore how these challenges translate into project management inefficiencies. Additionally, these studies mainly focus on general industries (construction, banking, and IT infrastructure), with limited emphasis on consultancy engineering projects.

2.3.3 Literature Review Focused on the Relationship Between Mediating Variables and Dependent Variables

These studies focus on how AI tools, once integrated into project management workflows, improve project efficiency, risk identification, collaboration, and decision-making.

Studies such as Belharet et al. (2020); Fridgeirsson et al. (2021); Ong & Uddin (2020) highlight that AI-driven project management reduces human errors and automates routine tasks, leading to significant time savings for project managers. Todorović (2022) and Wang (2023) further confirm that AI enhances predictive capabilities, allowing project teams to anticipate risks and optimize schedules. Another key finding is that AI contributes to improved resource allocation (Savio & Ali, 2023), enhanced project monitoring (Zadeh et al., 2024), and better risk mitigation (Alada, 2023). AI-driven decision support systems (Sheoraj & Sungkur, 2022) and real-time data analytics (Bah Esseme et al., 2025) also contribute to higher-quality project outcomes.

While these studies confirm AI's benefits in project management, they fail to examine the indirect role of AI as a mediating factor. There is little research that explores how AI tools bridge the gap between utilization challenges (Independent Variables) and project success (Dependent Variables).

2.3.4 General Studies in AI and Project Management

These studies provide broad discussions on AI and project management but do not explicitly investigate AI utilization challenges or project outcomes. Some focus solely on project management methodologies, exploring best practices, strategic planning, and leadership without integrating AI-related considerations. Others primarily examine AI technologies, such as ML and automation, without applying them to project management contexts. Additionally, some studies discuss AI's role in project management in a general sense, highlighting potential benefits and future trends but lacking empirical validation, structured frameworks, or direct analysis of AI utilization barriers and project success metrics.

2.3.5 The following (Table 1) explains the details of the previous studies and identifies the Gap in the previous studies;

Table 1.1 in (Appendix A) summarizes 63 key studies on AI in project management, classified into four categories:

1. Literature Review Focused on the Relationship Between Independent Variables and Dependent Variables.
2. Literature Review Focused on the Relationship Between Independent Variables and Mediating Variables.
3. Literature Review Focused on the Relationship Between Mediating Variables and Dependent Variables
4. General AI & Project Management Literature Review.

The table identifies three primary research gaps that this study addresses: limited design/consultancy focus, and absence of integrated mediation models. Detailed analyses and gap identification provided in Appendix A.

Previous Literature Review Commentary:

The studies reviewed highlight the growing influence of AI in project management across various industries. Existing research emphasizes AI's contributions to improving decision-making, efficiency, data analysis, risk identification, and project outcome quality. However, several challenges hinder AI utilization, including data privacy concerns, high implementation costs, resistance to change, ethical considerations, and lack of skilled resources.

2.3.5.1 *Similarities with Existing Research*

Several studies share commonalities with the present research, particularly in analyzing the impact of AI in project management. Existing studies have examined AI's contribution to data-driven decision-making and collaboration in construction contexts (Al-Ghamdi & Darman, 2022), its role in risk management and decision accuracy (Odejide & Edunjobi, 2024), and its influence on

scheduling, documentation, and process efficiency through project management information systems (Mahmood et al., 2023). Other work has demonstrated AI's value in predictive analytics for project planning and forecasting (Lishner & Shtub, 2022), its application in automating project communication through AI-powered chatbots (El-Khatib & Al Falasi, 2021), and its use in generating data-driven insights that support strategic decision-making (Wang et al., 2023). Collectively, these studies reinforce the argument that AI positively impacts project efficiency, risk management, and decision-making. However, while they explore AI's benefits, they do not fully examine the barriers to AI utilization, especially in design and consultancy engineering projects.

2.3.5.2 Differences from Existing Research

Although these studies demonstrate AI's diverse applications, they do not explore the practical utilization barriers and their impact on project performance, which this research aims to address. Existing work has largely focused on construction rather than design and consultancy contexts (Al-Ghamdi & Darman, 2022), on theoretical applications of AI rather than the practical barriers to its utilization (Odejide & Edunjobi, 2024), and on AI's presence within project management information systems without addressing how organizational factors shape its utilization (Mahmood et al., 2023). Similarly, other studies have concentrated narrowly on predictive modeling rather than developing a comprehensive framework for AI utilization challenges and project outcomes (Lishner & Shtub, 2022).

2.3.5.3 Key Gaps Identified in Existing Research

Key Gaps Identified in Existing Research

Despite the progress in AI applications, the literature review reveals three primary gaps that justify the need for this study.

Gap#1: Limited Focus on Design and Consultancy Projects

Most research on AI in project management primarily examines applications in construction, healthcare, and manufacturing and finance industries. Related work has explored AI in IT infrastructure and automation without extending these findings to specialized engineering consultancy sectors, and has highlighted continued uncertainty in AI utilization within project management more broadly. However, there remains a noticeable lack of studies specifically analyzing AI's impact on design and consultancy engineering projects, particularly within Saudi Arabia.

Gap#2: Lack of an Integrated Model Examining AI Utilization Factors and Outcomes

Many studies either focus on AI utilization barriers or AI's impact on project outcomes, but few comprehensively link both. To the researcher's knowledge, no study presents a structured model integrating independent (factors influencing AI utilization), mediating (AI-based project management), and dependent (project outcomes) variables. Prior research has examined decision-making and risk management using AI models without offering a structured framework connecting barriers, mediating practices, and outcomes, and has focused on AI in project management information systems without exploring how external factors such as resistance to change, cost, and ethical concerns influence utilization. Other work has used predictive modeling techniques to forecast project duration without examining how organizational, financial, or ethical barriers affect implementation. Similarly, the slow progress of AI in project management has been attributed to limited investment and a predominantly theoretical focus, without integrating utilization barriers with measurable outcomes, and data challenges such as explainability issues and data quality concerns have been identified without establishing a comprehensive model connecting these limitations to project success factors. Data privacy and security risks in AI-powered project management have also been addressed without connecting these concerns to AI's broader impact on outcomes, and AI's automation potential in construction project management has been studied with a focus limited to automation and real-time monitoring, without linking these barriers to project outcomes.

Gap#3: Insufficient Consideration of Context-Specific Challenges

Most studies offer general insights into AI utilization, but few provide practical recommendations tailored to specific industries. Moreover, ethical considerations, regulatory compliance, and organizational resistance in project-based sectors are not well documented. Data availability and quality issues have been identified as major implementation challenges, though without industry-specific applications for project management, and AI's role in decision-making and project data security has been discussed without recommendations tailored to the engineering consultancy sector. Similarly, AI utilization has been acknowledged as capable of enhancing project efficiency, though concerns regarding stakeholder satisfaction, data bias, and integration difficulties have been raised as requiring further research in consultancy projects specifically, and AI in project management information systems has been examined without addressing the ethical considerations or regulatory compliance issues that are critical in Saudi Arabia's engineering consultancy sector. Ethical risks of AI decision-making have also been highlighted without proposed guidelines for AI governance in project-based industries, and AI's impact on enterprise data management has been addressed without discussing how AI-specific challenges, such as resistance and infrastructure limitations, influence project execution.

Classification of the Research Gap

Following the taxonomy proposed by Miles (2017), which identifies seven recognized types of research gaps in the literature, the three gaps identified above can be classified as follows. Gap#1 (limited focus on design and consultancy projects, particularly within Saudi Arabia) represents a population gap, in that a specific professional and geographic population, practitioners in Saudi design and consultancy engineering firms, remains underrepresented in the existing evidence base, despite the growing relevance of AI adoption in this sector. Gap#2 (the absence of an integrated

model linking influencing factors, AI-based project management, and project outcomes) represents a methodological gap, since prior studies have examined these relationships in isolation rather than within a single mediation framework capable of testing direct, indirect, and combined effects simultaneously. Gap#3 (insufficient context-specific practical guidance) represents a practical-knowledge conflict gap, in that a body of general knowledge about AI's potential in project management exists, but this knowledge has not been translated into actionable guidance for the specific regulatory, cultural, and organizational conditions of Saudi Arabia's engineering consultancy sector. This study addresses all three gaps through its integrated conceptual model, its concurrent mixed-methods design, and its context-specific empirical focus.

2.4 Theoretical Integration of Study Variables

The five theoretical frameworks provide the conceptual foundation for this study's variables. **The Integrated AI Project Management Framework** (Weng, 2023) directly supports the mediating role of AI-based PM by linking AI tools to all seven dependent variables through core PM processes (planning, scheduling, reporting, risk management). **The AI-Driven Decision-Making Theory** underpins decision-making effectiveness and data analysis/insights by showing AI's enhancement of predictive analytics and risk assessment. **The Sustainable AI Utilization Model** explains the six independent variables (cost, infrastructure compatibility, workforce development, resistance to change, data privacy/security, ethical considerations) as critical utilization barriers. **The Collaborative AI Management Paradigm** connects AI-based PM to stakeholder communication and quality improvement across project stakeholders, while the **Adaptive AI Utilization Theory** (Bento et al., 2022) emphasizes dynamic organizational responses required for sustained AI effectiveness.

Relationship to the Technology Acceptance Model (TAM)

The Technology Acceptance Model (Davis, 1989) is one of the most widely applied frameworks for explaining individual technology adoption, proposing that perceived usefulness and perceived ease of use determine behavioral intention to use a technology, which in turn predicts actual usage. While TAM has informed much of the broader information-systems literature on AI adoption, this study adopted the Integrated AI Project Management Framework rather than TAM as its primary theoretical anchor, for three reasons. First, TAM's two core constructs address individual-level perceptions of a single technology, whereas this study examines six organizational and technical conditions operating at the firm level, a scope better served by a project-management-specific framework. Second, TAM does not incorporate a mediating mechanism analogous to AI-based project management utilization, which is central to this study's proposed pathway from organizational factors to project outcomes. Third, TAM was developed for general information-system adoption rather than the project-management-specific processes — scheduling, risk management, reporting — that the Integrated AI Project Management Framework addresses directly. Nonetheless, TAM's core insight, that perceived usefulness and ease of use drive adoption, is reflected indirectly in this study's workforce development and infrastructure compatibility factors, both of which capture organizational conditions that shape how easily and usefully AI tools can be applied in practice.

2.5 Chapter 2 Summary

Chapter 2 developed the theoretical framework using the Integrated AI Project Management Framework, AI-Driven Decision-Making Theory, Sustainable AI Utilization Model, and Collaborative AI Management Paradigm to operationalize study variables. Six independent variables (Data privacy and security, Resistance to change, Costs of implementation, Compatibility with existing infrastructure, Workforce development, Ethical considerations) were defined per the literature. AI-based project management mediators included automation, predictive analytics, PMIS integration; dependent variables covered Enhancing Decision-Making, Project Quality, Data Collection Accuracy, Data Analysis, Risk Identification Accuracy, Saving Time for Project Manager Operation Efficiency, and Effective Communication. The researcher perspective emphasized AI's inevitability for repetitive project tasks, positioning this mediation model to fill Saudi design/consultancy literature gaps identified in Chapter 1.

CHAPTER 3

3 Research Methods and Procedures (Methodology)

3.1 Research Methodology (Approach)

3.1.1 Research Design Framework Description

This study employed a mixed-method research design, integrating quantitative survey data with qualitative insights from expert interviews. This approach was justified by the need to explore both the independent factors influencing the utilization of AI-based project management and the measurable outcomes resulting from its integration in design and consultancy engineering projects. The study was grounded in a conceptual model that identified and categorized the three sets of variables: independent factors influencing AI utilization, the mediating role of AI-based project management practices, and the resulting project management outcomes. The model served as the theoretical foundation for both instrument design and data analysis. This study employed a concurrent triangulation mixed-methods design (Creswell & Plano Clark, 2018), in which quantitative surveys (n=103) and qualitative interviews (n=10) were collected simultaneously during September–November 2025 without linking participants. Both datasets were analyzed in parallel, then integrated at the interpretation stage through systematic triangulation to validate quantitative patterns.

The quantitative phase provided statistically validated evidence on the relationships among influencing factors, AI utilization, and project outcomes. Meanwhile, the qualitative phase added depth by capturing real-world insights, challenges, and enablers from industry experts. Both phases proceeded simultaneously, with qualitative findings used post-hoc to triangulate and interpret quantitative patterns. This concurrent explanatory design was justified by the complex nature of AI adoption, which required both statistical validation of relationships and contextual understanding of implementation barriers and enablers in Saudi design firms. Together, these methods ensured a comprehensive and empirically grounded understanding of the dynamics shaping AI-based project management in the Saudi consultancy and design sector.

Within the quantitative component of the concurrent mixed-methods design, structural equation modeling (SEM) was conducted using IBM SPSS Amos to test the hypothesized mediation relationships. The analysis followed a two-step approach comprising measurement-model evaluation and structural-model assessment.

1. Measurement Model: Confirmatory factor analysis (CFA) was conducted to evaluate the measurement properties of all constructs. The measurement model was assessed using CFA rather than a sequential exploratory factor analysis followed by CFA. This decision was based on the theory-driven structure of the study, in which the constructs and their indicators were specified in advance from the theoretical framework and previous literature. The questionnaire was also reviewed by subject-matter experts and pilot-tested before the main survey. CFA was therefore

used to assess the hypothesized measurement structure through factor loadings, composite reliability, convergent validity, discriminant validity, and global model-fit indices.

Exploratory factor analysis (EFA) was not conducted before CFA. Given the achieved sample size of 103, dividing the sample into separate EFA and CFA subsamples would have reduced the statistical adequacy of both analyses and would not have provided strong independent validation. The CFA results were therefore interpreted as a test of the theory-specified measurement structure rather than as an exploratory discovery of the factor structure.

2. Structural Model: Path analysis was used to estimate the hypothesized structural pathways by testing the following relationships:

- **Direct effects of the independent variables on project outcomes:** Standardized path coefficients were estimated to assess whether the six independent variables — data privacy and security, resistance to change, cost of AI implementation, compatibility with existing infrastructure, workforce development, and ethical considerations — directly influenced the seven project-management outcomes: decision-making, project quality, data collection accuracy, data analysis, risk identification accuracy, time saving, and communication.
- **Direct effects of the independent variables on AI-based project-management utilization:** Path coefficients were estimated to determine the extent to which each independent variable influenced the adoption and utilization of AI-based project management.
- **Indirect effects through mediation:** Bootstrap confidence intervals were calculated for the indirect pathways to test whether the effects of the independent variables on project outcomes operated through AI-based project management. Specifically, the analysis examined whether the influencing factors affected the relevant project-management outcomes indirectly by influencing AI-PM utilization, which subsequently influenced those outcomes.

All path coefficients were reported with standard errors and 95% confidence intervals. Statistical significance was assessed using two-tailed tests at $\alpha = .05$. R^2 values were reported to indicate the proportion of variance explained in each relevant endogenous variable.

Model fit was evaluated using the chi-square-to-degrees-of-freedom ratio (χ^2/df), the Comparative Fit Index (CFI), the Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR). The criteria used were $CFI \geq 0.90$, $RMSEA \leq 0.08$, and $SRMR \leq 0.08$.

3.1.2 Justification of Methodology Choice:

This research applied a mixed-method research approach, integrating both quantitative and qualitative data collection and analysis. The rationale behind this choice stemmed from the complex nature of the research objectives, which aimed to identify factors influencing AI utilization, measure its effect on project outcomes, and analyze the mediating role of AI-based project management in design and consultancy engineering projects.

Furthermore, the **mixed-method research design** was chosen to bridge the gap between theoretical insights and practical applications in AI-based project management. This dual approach ensured that the study captured both perceptions and measurable effects, offering a holistic analysis.

The quantitative component involved the distribution of structured questionnaires to a wide sample of professionals in Saudi Arabia's engineering consultancy sector. This allowed the collection of statistically analyzable data on the relationship between the identified variables.

The qualitative component was based on semi-structured interviews with subject-matter experts and decision-makers in AI-based project management. This provided in-depth insight into contextual factors, real-world challenges, and practical strategies, supporting a deeper understanding of the utilization process and interpretation of survey results.

3.1.3 Limitations of Concurrent Design and Mitigation Strategies

While the concurrent mixed-methods design provided complementary insights, it presented several methodological challenges that were actively addressed:

Potential Limitations:

1. **Integration Challenges:** Concurrent collection can create difficulties in integrating findings if quantitative and qualitative results diverge.
 - **Mitigation:** A specific triangulation protocol was developed a priori (full details in Appendix B):
 - Statistical significance at the $p < 0.05$ level, plus effect sizes (R^2), determined the strength and direction of relationships.
 - Qualitative validation required agreement in at least 7 of 10 interviews for any given theme.
 - Divergence rule: Quantitative effect sizes served as the primary evidence, while qualitative findings explained the context only.

- **Priority:** Statistical power took precedence over qualitative thematic narratives.
2. **Timing Discrepancy:** Simultaneous data collection from different respondent groups (survey vs. interview participants) may capture different organizational contexts or timepoints.
 - **Mitigation:** Both quantitative and qualitative data collection occurred concurrently within the same three-month period (September–November 2025), minimizing temporal drift. Interview participants included representatives from organizations that also completed the survey, enabling direct contextualization.
 3. **Prioritization Ambiguity:** Concurrent designs require clear prioritization rules when findings conflict. Equal weight to both methods may mask statistical significance with qualitative anecdotes
 - **Mitigation:** A priori prioritization established that statistical significance ($p < 0.05$) and effect sizes (R^2) would drive interpretation, with qualitative findings serving validation and contextual enrichment rather than primary evidence.
 4. **Analyst Bias:** Managing two independent analytical pathways increases the risk of analyst bias or selective interpretation favoring one method.
 - **Mitigation:** Analysis was conducted using established, transparent protocols (SPSS AMOS for quantitative; thematic coding for qualitative). Preliminary findings were reviewed by independent research assistants before integration.
 5. **Quantitative Response Rate and Nonresponse Bias:** Of the 250 questionnaires distributed, 103 were completed and returned, yielding a response rate of 41.2%. Although the achieved sample exceeded the minimum sample size indicated by the a priori power analysis, the response rate created a possibility of nonresponse bias, because respondents may have differed from nonrespondents in their AI familiarity, organizational role, or level of interest in digital transformation.
 - **Mitigation:** The study reported the response rate transparently, used follow-up contact with a subset of nonrespondents to identify the main reason for nonparticipation, and compared the available contextual information without identifying obvious differences. The achieved sample was also evaluated against the G*Power minimum requirement, and the sample characteristics were described in detail. Nevertheless, the possibility of nonresponse bias could not be completely excluded, and the generalizability of the findings is therefore interpreted with caution.
 6. **Measurement-Validation Limitation:** The study did not conduct a sequential EFA–CFA procedure. The measurement structure was specified from the theoretical framework and previous literature, then assessed through CFA after expert review and pilot testing. However, because the instrument included study-specific operationalization and the main

quantitative sample comprised 103 respondents, the measurement structure was not independently explored and confirmed using separate samples.

- **Mitigation:** The study used expert review, pilot testing, internal-consistency assessment, CFA, factor-loading analysis, composite reliability, convergent validity, and discriminant-validity assessment to evaluate the instrument. Future studies should replicate the measurement model using a larger sample and, where appropriate, conduct EFA and CFA on independent samples.

Overall Assessment: These limitations were not eliminated but were actively managed through systematic protocols, temporal alignment, and transparent prioritization. The resulting triangulation section demonstrates strong convergence, suggesting that concurrent design limitations did not substantially compromise the validity of the findings.

3.1.4 Research Design-Question Alignment

This dual approach ensured that the findings were both statistically valid and contextually grounded, enhancing the reliability and relevance of the research conclusions.

The mixed-methods design directly addressed the three research questions:

- **RQ1:** What factors influence AI-based project management utilization?

Note: Addressed via quantitative analysis of independent variables' correlations and SEM direct-effects pathways.

- **RQ2:** What are the outcomes of AI-based project management?

Note: Addressed via quantitative dependent-variable measurement and qualitative practitioner perceptions.

- **RQ3:** How does AI-based project management mediate the relationship between influencing factors and project outcomes?

Note: Addressed via quantitative mediation analysis (indirect effects) and qualitative exploration of implementation mechanisms.

Quantitative SEM testing provided statistical significance and effect sizes; qualitative interviews explained the "why" and "how" behind these relationships, uncovering contextual factors unique to Saudi engineering firms.

This research employed a mixed-method research design in which structured quantitative data formed the basis for hypothesis testing, while qualitative interviews offered contextual support and

interpretation. The study made a theoretical contribution by proposing and validating a model that links influencing factors, AI-based project management practices, and project outcomes through mediation analysis. On the practical level, it delivers actionable recommendations tailored to the specific context of Saudi Arabia's design and consultancy engineering sector.

3.2 Research Hypotheses

Based on the conceptual model presented in Figure 1 of Chapter 2 and reviewed within Chapter 3's framework, the following hypotheses were formally tested in Chapter 4:

- **H1: Impact of Independent Variables on Dependent Variables ("Project Outcomes")**

no.	Sub-Hypothesis
1	H1A: Data privacy and security concerns significantly influence project outcomes in design and consultancy engineering projects.
2	H1B: Resistance to change significantly influences project outcomes in design and consultancy engineering projects.
3	H1C: Costs of AI implementation significantly influence project outcomes in design and consultancy engineering projects.
4	H1D: The compatibility of AI tools with existing infrastructure significantly influences project outcomes in design and consultancy engineering projects.
5	H1E: Workforce development significantly influences project outcomes in design and consultancy engineering projects.
6	H1F: Ethical considerations significantly influence project outcomes in design and consultancy engineering projects.

- **H2: Impact of Independent Variables on the Mediating Variable ("AI-Based Project Management")**

no.	Sub-Hypothesis
1	H2A: Data privacy and security significantly influence the utilization of AI-based project management practices in design and consultancy projects.
2	H2B: Resistance to change significantly influences the utilization of AI-based project management practices in design and consultancy projects.
3	H2C: Costs of implementation significantly influence the utilization of AI-based project management practices in design and consultancy projects.
4	H2D: Compatibility with existing infrastructure significantly influences the utilization of AI-based project management practices in design and consultancy projects.
5	H2E: Workforce development significantly influences the utilization of AI-based project management practices in design and consultancy projects.

6	H2F: Ethical considerations significantly influence the utilization of AI-based project management practices in design and consultancy projects.
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- **H3: Impact of the Mediating Variable ("AI-Based Project Management") on Project Outcomes**

no.	Sub-Hypothesis
1	H3A: The utilization of AI-based project management practices significantly improves decision-making in design and consultancy projects.
2	H3B: The utilization of AI-based project management practices significantly improves project quality in design and consultancy projects.
3	H3C: The utilization of AI-based project management practices significantly improves data collection accuracy in design and consultancy projects.
4	H3D: The utilization of AI-based project management practices significantly improves data analysis and insight generation in design and consultancy projects.
5	H3E: The utilization of AI-based project management practices significantly improves risk identification and mitigation in design and consultancy projects.
6	H3F: The utilization of AI-based project management practices significantly reduces time spent by project managers on routine tasks in design and consultancy projects.
7	H3G: The utilization of AI-based project management practices significantly improves communication among stakeholders in design and consultancy projects.

- **H4: The utilization of AI-based project management mediates the relationship between influencing factors and project outcomes in design and consultancy projects.**

Research Hypotheses Conceptualization: These hypotheses reflect a three-level causal structure:

- External contextual and organizational factors (independent variables).
- The degree of AI-based PM implementation (mediating variable).
- Measurable project-management outcomes (dependent variables).

The mediation hypotheses (H3) tested whether the influencing factors' effects on outcomes were transmitted through AI-based PM utilization, supporting the theoretical model's causal logic.

3.3 Study Population and Sampling:

3.3.1 Study Population:

The target population consisted of professionals working in design and consultancy engineering firms in Saudi Arabia who were involved in project management, organizational decision-making, digital transformation, or the utilization of AI-supported project-management tools. Eligible participants included project directors, project managers, engineers, department leaders, and other professionals with direct knowledge of project-management processes and AI utilization.

A single official national register identifying the total number of employees who met these criteria was not available. Therefore, the study did not claim a statistically enumerated national population. Instead, the population was defined operationally according to the eligibility criteria above, and purposive access sampling was used to reach information-rich participants through professional networks and engineering firms. This limitation restricts statistical generalization to the wider population of all employees in Saudi design and consultancy engineering companies. While the broader environment consists of a diverse range of firms, this study prioritized the targeted selection of knowledgeable participants to explore the dynamics of AI use in real-world contexts.

A total of 250 questionnaires were distributed through professional networks, WhatsApp groups, and direct contacts with professionals working in Saudi design and consultancy engineering firms. Of these, 103 completed questionnaires were returned, producing a response rate of 41.2%. The 103 responses exceeded the minimum required sample size of 68 estimated through the a priori G*Power analysis. Follow-up contact with 30 nonrespondents indicated that time constraints were the main reported reason for nonparticipation. Because nonresponse bias could not be tested conclusively, the response rate is acknowledged as a limitation, and the generalizability of the findings is interpreted with appropriate caution.

3.3.2 Quantitative Study Sample Adequacy & Justification:

Participants were purposively selected to capture the perspectives of professionals with direct involvement in AI-based project management in Saudi design and consultancy engineering firms. Key participant roles included project directors, managers, engineers, department leads, and decision-makers with relevant AI expertise. This sampling approach aimed at collecting rich, context-specific data, emphasizing variation by organizational size, AI maturity, and sector specialization. Demographic information, such as role, experience, and organizational background, was collected to support a nuanced analysis of AI utilization factors and outcomes.

The study sample comprised $n = 103$ professionals from Saudi Arabia's design and consultancy engineering firms. This sample size was determined through a priori power analysis using G*Power 3.1.9.7, with an anticipated squared multiple correlation ($H1 \rho^2$) of 0.30, a null-hypothesis value ($H0 \rho^2$) of 0, $\alpha = 0.05$, and power = 0.95, yielding a minimum required $n = 68$. The actual sample of 103 exceeded this requirement and provided adequate power for SEM analysis, which typically requires 10–20 cases per estimated parameter.

The study employed two complementary approaches to justify sample adequacy:

1. **A Priori Power Analysis:** Using G*Power 3.1.9.7 (Exact — Linear multiple regression: Random model), a priori power analysis was conducted with six independent-variable predictors (representing the study's six influencing factors), an anticipated squared multiple correlation (H1 ρ^2) of 0.30, a null-hypothesis value (H0 ρ^2) of 0, $\alpha = 0.05$, and power = 0.95. This analysis yielded a required minimum sample size of $n = 68$ (lower critical $R^2 = 0.0194562$; upper critical $R^2 = 0.2051260$; actual power = 0.9531301).
2. **Confirmatory Factor Analysis (CFA) Fit Index Assessment:** CFA is more stringent than regression in its sample requirements. Following the recommendations of Hu and Bentler (1999), Browne and Cudeck (1993), and Kline (2016), the study's CFA-based SEM model was evaluated using global fit indices. The acceptable fit thresholds were:
 - Comparative Fit Index (CFI): Values ≥ 0.90 indicate acceptable fit; ≥ 0.95 indicate excellent fit (Hu & Bentler, 1999).
 - Root Mean Square Error of Approximation (RMSEA): Values ≤ 0.08 indicate acceptable fit; ≤ 0.06 indicate good fit (Browne & Cudeck, 1993).
 - Chi-Square to Degrees of Freedom Ratio (χ^2/df): Values ≤ 3.0 are acceptable; ≤ 2.0 indicate good fit (Kline, 2016).

The final sample of $n = 103$ respondents exceeded both the minimum sample size from the power analysis ($n = 68$) and the widely cited minimum SEM guideline of approximately five cases per estimated parameter (Bentler & Chou, 1987). Given that the SEM model included 20 estimated parameters, the sample of 103 respondents satisfied this minimum criterion ($103/20 = 5.15$ cases per parameter). While more conservative guidance recommends 10–20 cases per parameter, the achieved ratio meets the threshold widely regarded as an acceptable minimum for confirmatory SEM models, particularly given the theory-driven, expert-reviewed, and pilot-tested nature of the measurement instrument. The model fit indices achieved with $n = 103$ are presented in Chapter 4 and confirm sample adequacy.

3.3.3 Quantitative Sample Size Calculation

An a priori power analysis was conducted using G*Power version 3.1.9.7 to determine the minimum sample size required for the quantitative analysis. The analysis used an exact linear multiple-regression model with a random-effects framework and an exact distribution.

The analysis used a two-tailed test, an anticipated squared multiple correlation of $R^2 = 0.30$, a null-hypothesis value of $R^2 = 0$, a significance level of $\alpha = .05$, statistical power of $1 - \beta = .95$, and six predictors.

The analysis indicated a required total sample size of 68 participants, with an estimated actual power of 0.953. The lower and upper critical R^2 values were 0.0194562 and 0.2051260, respectively. The software-generated sample-size calculation is provided in Appendix B as Figure 2.

3.3.4 Qualitative Study Sample Adequacy & Justification:

The qualitative component employed purposive sampling to select expert interviewees from Saudi design and consultancy engineering firms, based on their expertise and involvement in AI-based project management. Selection criteria included leadership or technical roles, direct engagement in strategic planning, operational decision-making, or technical implementation of AI and digital project-management tools, and organizational affiliation to ensure relevant context. Interviews included participants across seniority levels — top management (e.g., directors, CEOs), middle management (e.g., senior project managers), and technical professionals (AI experts, engineers) — to capture diverse, rich perspectives.

A total of 10 semi-structured interviews were conducted with participants meeting the following selection criteria:

- **Organizational Role:** Leadership positions (directors, CEOs) or technical specialist roles (AI implementation leads, senior project managers).
- **Experience Requirement:** A minimum of five years of experience in project management and at least two years of direct or indirect engagement with AI tools.
- **Decision-Making Involvement:** Direct engagement in strategic planning, operational decision-making, or technical implementation of AI and digital project-management tools.
- **Organizational Representation:** Affiliation with design and consultancy engineering firms operating in Saudi Arabia.

Interviewees were selected to ensure diversity in organizational size, AI maturity level, and implementation experience. Sampling continued until thematic saturation was achieved (no new themes emerging across two to three consecutive interviews), which occurred by interview 10, with no new substantive themes emerging after interview 7. Following Braun and Clarke (2019) and Fugard and Potts (2015), sampling ceased when no new substantive themes emerged from consecutive interviews — a criterion typically achieved within 8–12 interviews for focused exploratory research. Furthermore, a systematic review of mixed-methods studies in organizational technology adoption (Creswell & Plano Clark, 2018; Venkatesh et al., 2013) identified that qualitative samples in comparable research typically ranged from 8–15 expert interviews. Morse (2000) recommends minimum sample sizes based on design complexity: 6–8 participants for exploratory descriptive designs of moderate complexity, and 12–20 participants for more complex phenomena. Given this study's mediation-hypothesis complexity, a target range of 10–12 participants was established a priori, and the achieved sample of 10 interviews fell within this range.

3.3.5 Addressing Potential Sampling Bias

The survey distribution through professional WhatsApp groups and the researcher's network may have introduced some sampling bias toward accessible and digitally connected project-management professionals. This limitation was addressed by ensuring that the sample largely represented senior practitioners in Saudi engineering firms, included participants from different

organizational contexts, and was supplemented by qualitative triangulation with 10 expert interviews. Standard statistical checks were also applied to support the robustness of the quantitative analysis.

3.3.6 Concurrent Triangulation Design Justification

This study adopted a concurrent triangulation mixed-methods design (Creswell & Plano Clark, 2018), in which quantitative survey data (n=103) and qualitative expert interviews (n=10) were collected simultaneously. This design was selected over sequential approaches for three key reasons relevant to examining complex AI-project management relationships:

1. Simultaneity captures real-time convergence: AI implementation in engineering projects is dynamic. Concurrent data collection ensured that quantitative (SEM results) and qualitative (expert perceptions) data reflected the same temporal context, enabling direct triangulation (Creswell & Plano Clark, 2018).

2. Convergent validation of complex relationships: The study's mediation model (6 IVs → AI-PM → 7 DVs) required simultaneous cross-validation. Concurrent design allowed immediate comparison of statistical paths (β coefficients) with expert interpretations, strengthening causal inference (Teddlie & Tashakkori, 2009).

3. Practical efficiency in organizational context: Sequential designs risk participant dropout and contextual drift in fast-paced engineering firms. Concurrent design maximized response rates and contextual consistency (Johnson & Onwuegbuzie, 2004).

3.4 Construction of Data Collection Instruments

3.4.1 Instrument Overview

To achieve the research objectives and test the proposed hypotheses, this study applied a mixed-method research design, utilizing both a structured questionnaire and a semi-structured interview guide as the primary data collection instruments.

- The structured questionnaire represented the quantitative tool, capturing measurable data across the three core variable groups: factors influencing AI utilization (independent variables), AI-based project management practices (mediating variable), and project management outcomes (dependent variables).
- The semi-structured interviews served as the qualitative instrument, providing rich contextual insight into the challenges, benefits, and strategic considerations involved in AI-based project management.

This dual-instrument design ensured a comprehensive analysis that included both empirical validation and in-depth exploration of real-world experiences.

3.4.2 Quantitative Instrument (Questionnaire Structure)

The questionnaire was designed using closed-ended questions on a five-point Likert scale to assess agreement, frequency, or impact perception. Additionally, a small set of open-ended questions was included to enrich the quantitative data with narrative insights aligned with key research objectives. The questionnaire comprised five domains:

1. **Demographic and Organizational Information:** Captured participants' roles, experience, company size, AI familiarity, and current AI usage in project management.
2. **Independent Variables (Influencing Factors):** Measured the extent to which the following six factors influenced the utilization of AI-based project management in design and consultancy engineering projects:
 - Data Privacy and Security
 - Resistance to Change
 - Cost of AI Implementation
 - Compatibility with Existing Infrastructure
 - Workforce Development
 - Ethical Considerations
3. **Mediating Variable (AI-Based Project Management):** Evaluated the extent to which AI tools were utilized in core project-management tasks such as scheduling, reporting, risk handling, collaboration, and coordination.
4. **Dependent Variables (Project Management Outcomes):** Assessed the perceived outcomes of AI-based project management, including:
 - Decision-making
 - Project quality
 - Data collection accuracy
 - Data analysis and insight generation
 - Risk identification
 - Time efficiency
 - Collaboration and communication
5. **Open-Ended Questions:** A set of open-ended questions was included at the end of the structured questionnaire, designed to capture narrative insights that may not have been fully expressed through Likert-scale responses. Participants were encouraged to share their

views on barriers, enablers, perceived benefits, and strategic recommendations regarding the utilization of AI-based project management practices. The responses underwent thematic coding, in which each response was analyzed and mapped to predefined dependent-variable (DV) themes, such as decision-making, project quality, data collection accuracy, data analysis, risk identification, time efficiency, and collaboration and communication. At the same time, the underlying factors mentioned in the responses — including technical, organizational, or ethical challenges — were treated as influencing factors (linked to the independent variables). This structure allowed the researcher to identify how specific influencing factors influenced particular outcomes, based on participants' own words. The following logic was applied during analysis:

- Open-ended responses were grouped under themes representing the project-management outcomes (DVs).
- The content of each response was interpreted to identify the influencing factor (IV) it addressed, along with the direction of impact (e.g., enabling, limiting, improving).
- These results were used to triangulate the quantitative findings derived from SEM, reinforcing the validity and contextual depth of the observed relationships.

To structure this analysis, a coding-matrix example was developed to guide the mapping process, as illustrated in the following table:

Open-Ended Responses (Related to Influencing Factors – IVs)	Mapped DV Theme (Project Outcome)
"The high cost of AI implementation makes it difficult to adopt comprehensive project tools."	Project Quality — Negative impact
"Our AI tools help collect real-time data from multiple sources with improved consistency."	Data Collection Accuracy — Positive impact
"Due to outdated infrastructure, AI-based systems cannot integrate fully with our current tools."	Time Efficiency — Negative impact
"Once integrated, the AI platform improved team communication by providing shared dashboards."	Collaboration & Communication — Positive impact
"Most of our engineers are not trained in AI-based forecasting tools, which slows us down."	Time Efficiency — Negative impact
"We use AI to flag early-stage risks through data pattern recognition."	Risk Identification — Positive impact
"It's hard to make decisions without clear ethical frameworks for AI usage in client-facing projects."	Decision-Making — Negative impact

"AI tools enabled faster scenario analysis, which improved our ability to make strategic project decisions."	Decision-Making — Positive impact
"Data privacy regulations are too vague, which restricts how much we can automate."	Data Analysis — Negative impact
"AI utilization helped us improve how we organize and analyze project reports and KPIs."	Data Analysis — Positive impact
"The AI assistant helped us identify and resolve quality issues in design documentation."	Project Quality — Positive impact
"Resistance from senior management delayed AI rollout, which influenced our ability to track and respond to project risks."	Risk Identification — Negative impact
"Even with limited AI features, our team was able to automate repetitive data entry tasks."	Data Collection Accuracy — Positive impact
"Collaboration improved once we used AI-enabled project timelines that synced with team calendars."	Collaboration & Communication — Positive impact

This coding approach allowed the open-ended data to directly reinforce and expand the findings from the quantitative model (via SEM), following a triangulation strategy. It also ensured that the qualitative insights remained tightly integrated with the conceptual framework and research objectives, contributing both explanatory richness and methodological rigor.

3.4.3 Questionnaire Development Sources

The questionnaire was developed by drawing on key ideas from the studies reviewed in Chapter 2. The following represent some key sources from Chapter 2 used to develop the questionnaire: for the independent variables — data privacy and security, implementation costs, resistance to change, infrastructure compatibility, workforce training, and ethical concerns — the study drew on the AI adoption barriers discussed by Alshaikhi and Khayyat (2021), Kelepouris (2023), and Weng (2023). The mediating variable, AI-based project management utilization, was developed directly from the frameworks in Weng (2023), Alshaikhi and Khayyat (2021), and Kelepouris (2023). Finally, the dependent variables covering decision-making, project quality, data accuracy, analysis improvement, risk identification, time savings, and communication were shaped by the practical outcomes discussed by Alada (2023), El-Khatib and Al Falasi (2021), Korke et al. (2023), Tubman (2022), and Belharet et al. (2020). Experts reviewed the questionnaire for content relevance, and a pilot test confirmed its reliability across all sections (detailed in Chapter 4).

3.4.4 Qualitative Instrument (Expert Interview Guide)

To supplement the quantitative findings and provide contextual depth, a semi-structured interview guide was developed based on the conceptual model and research objectives. This tool enabled a deeper understanding of:

- Perceptions of AI utilization in project management practices.

- Challenges and factors related to data security, workforce capability, and ethical concerns.
- Organizational readiness and infrastructure compatibility.
- Decision-making dynamics and time efficiency linked to AI.
- Real examples from practice in design and consultancy engineering projects.
- Industry-specific reflections, especially within Saudi firms.

Interviews were conducted in person or virtually, depending on participant availability and logistical feasibility. Participants included top management, middle management, and technical professionals from Saudi Arabia's leading design and consultancy firms.

3.4.5 Instrument Validation and Reliability

The questionnaire was first reviewed by one PhD supervisor, two senior project managers, and one AI specialist familiar with Saudi engineering firms. They identified a few unclear questions and suggested rewording three items. The questionnaire was then piloted with 15 project managers (8–15 years of experience); no questions were dropped, and only minor wording fixes and Google Forms adjustments were made. Pilot data were analyzed in SPSS, confirming acceptable alphas (> 0.70) before main deployment; final study reliability remained strong, with all Cronbach's alphas exceeding 0.70.

• Questionnaire (Quantitative Instrument)

Content validity was established to ensure that the items appropriately reflected the study's independent, mediating, and dependent variables. A pilot study was conducted with a small representative sample of participants from the target population. The pilot tested:

- Clarity of wording
- Logical flow
- Response time
- Consistency
- Content validity (via expert feedback)

This validation process ensured that the questionnaire produced statistically sound and meaningful data for hypothesis testing.

Interview Guide (Qualitative Instrument)

The semi-structured interview guide was validated through expert review to ensure relevance, neutrality, and clarity of the open-ended questions. It was pilot-tested with a small number of participants to verify:

- Interview flow and timing
- Comprehension and interpretation of questions
- Thematic alignment with the study's objectives and conceptual framework

Following the pilot, minor revisions were applied to enhance the instrument's integrity before full deployment.

3.5 Identification of Study Variables

This section defines the key variables that constitute the foundation of the research model. The study framework is structured around three main types of variables:

- **Independent Variables (IVs):** Factors influencing the utilization of AI tools in project management.
- **Mediating Variable (MV):** AI-based project management.
- **Dependent Variables (DVs):** Project management outcomes.

3.5.1.1 *Independent Variables (IVs): Factors Influencing the utilization of AI Tools*

These variables reflect organizational, technical, and ethical dimensions that influence the utilization of AI-based project management practices in design and consultancy engineering projects. The six independent variables identified are:

1. Data Privacy and Security
2. Resistance to Change
3. Cost of AI Implementation
4. Compatibility with Existing Infrastructure
5. Workforce Development (Training and Skills)
6. Ethical Considerations — this variable measures organizational awareness, adherence, and proactive management of ethical issues in AI utilization for project management. It was operationalized through questionnaire items addressing:
 - Presence and enforcement of formal AI ethics policies (e.g., data usage, transparency, bias mitigation).
 - Compliance with national and sectoral AI governance guidelines (e.g., SDAIA's AI Ethics Principles).
 - Availability of training or awareness programs on ethical AI usage for employees.
 - Perceptions of fairness, accountability, and transparency in AI-driven decision-making.

Each of these variables was operationalized using multiple items on a five-point Likert scale. These independent variables formed the foundation for understanding the drivers and barriers that influence the extent to which AI can be effectively utilized in project-management processes.

3.5.1.2 Mediating Variable (MV): AI-Based Project Management

The mediating variable, AI-based project management, captured the degree to which AI tools were embedded in core project-management practices, including planning and scheduling, documentation and reporting, resource allocation, risk analysis, and team collaboration. This construct acted as a bridge between the influencing factors (IVs) and project outcomes (DVs), reflecting how AI integration transformed workflows and mediated their effect on performance outcomes. Its role was empirically tested through mediation analysis, capturing dimensions such as:

- Planning and scheduling
- Documentation and progress reporting
- Resource forecasting and allocation
- Risk analysis and decision support
- Team communication and collaboration

These dimensions were selected based on established literature on AI applications in project management and were reflected across the study's data collection tools to ensure construct alignment.

This variable was central to understanding how AI reshapes management workflows and mediates the influence of external factors on performance outcomes. The mediating role of this variable was statistically tested using mediation analysis techniques.

3.5.1.3 Dependent Variables (DVs): Project Management Outcomes

These variables represent the results and benefits associated with the utilization of AI-based project management. They focus on performance, efficiency, quality, and collaboration outcomes achieved through AI integration. The seven dependent variables are:

1. Decision-Making
2. Project Quality
3. Data Collection Accuracy
4. Data Analysis
5. Risk Identification Accuracy
6. Time Saving
7. Communication

Each variable was measured through structured items designed to evaluate how the utilization of AI-based project management influenced key project performance indicators. The data were gathered via the quantitative questionnaire and supported by qualitative insights obtained through expert interviews.

3.6 Implementation Procedures

This section details the practical steps followed to carry out the study, from instrument development through data collection and validation. This procedure ensured compliance with ethical research principles and academic integrity.

3.6.1 Instrument Development

Questionnaire Design (Quantitative Tool)

The structured questionnaire was developed to measure the three main variable sets defined in the conceptual framework — independent variables, the mediating variable, and dependent variables — through dedicated domains and supporting demographic and qualitative items:

1. **Demographic Information** (e.g., position, experience, company size, familiarity with AI).
2. **Independent Variables** — items measuring data privacy, cost concerns, resistance to change, etc.
3. **Mediating Variable** — items exploring how AI was embedded in project management.
4. **Dependent Variables** — items measuring project outcomes influenced by AI.
5. **Open-Ended Questions** — designed to capture deeper qualitative insights that may not have emerged from fixed-response questions.

A five-point Likert scale was used for all closed-ended items to ensure clarity, comparability, and statistical validity.

Semi-Structured Interview Guide (Qualitative Tool)

To complement the quantitative data, a semi-structured interview guide was designed, including open-ended questions aligned with each of the three variable types:

- Challenges related to each independent variable
- Reflections on AI-based project management practices
- Perceptions of the resulting project outcomes

This qualitative instrument enabled deeper exploration of emerging themes and provided context for interpreting quantitative findings.

- **Pilot Testing**

Questionnaire Pilot Testing:

The structured questionnaire underwent pilot testing with a small sample (n=15) of professionals working in Saudi design and consultancy engineering firms, selected separately from the main study sample. The pilot assessed:

1. Clarity of item wording and comprehensibility
2. Logical flow and sequence of questions
3. Estimated completion time (target: 15–20 minutes)
4. Appropriateness of Likert-scale response options
5. Identification of redundant or confusing items
6. Content validity through expert feedback

Pilot participants completed the questionnaire and then took part in a brief feedback discussion about their experience.

Reliability Threshold:

Cronbach's Alpha was calculated for each construct during pilot testing. The acceptable threshold was $\alpha \geq 0.70$ for each construct. Since all constructs met this threshold in the pilot, no items were removed; only minor wording refinements were made based on pilot feedback.

Interview Guide Pilot Testing:

The semi-structured interview guide was reviewed and refined through consultation with academic and industry experts prior to full deployment. Pilot testing verified:

1. Interview flow and logical progression of questions
2. Comprehension and clarity of open-ended questions
3. Appropriate level of neutrality (avoiding leading questions)
4. Alignment of interview questions with study objectives and theoretical framework
5. Estimated interview duration (target: 45–60 minutes)
6. Identification of any sensitive or problematic question phrasing

Three pilot interviews were conducted with interviewees similar to the target sample. These pilot interviews were analyzed, and the interview guide was refined based on the emergent insights.

Outcome of Pilot Testing:

Following pilot testing, final versions of both the questionnaire and interview guide were cleared for full-scale deployment, with documented revisions from pilot feedback integrated.

3.6.2 Ethical Considerations

Participants were purposively selected based on their expertise related to AI-based project management. Informed consent was obtained from all participants prior to their voluntary participation in the study. Data confidentiality and anonymity were stringently maintained throughout the research process. Interviews were audio-recorded only with participants' consent, and participants were informed of their right to decline recording without any repercussions.

This study strictly complied with ethical guidelines approved by the university, implementing the following measures:

- Participants were fully informed of the study's purpose, scope, and voluntary nature.
- Written informed consent was obtained before data collection.
- No identifying personal or organizational information was collected, ensuring anonymity and confidentiality.
- Participants retained the right to decline audio recording of interviews.

3.6.3 Questionnaire Distribution and Data Collection

Quantitative Data Collection (Questionnaire):

The structured questionnaire was distributed electronically via the following channels:

- Email to existing professional networks
- Professional platforms (LinkedIn, WhatsApp)
- Company directories of participating Saudi design and consultancy engineering firms

Target participants were engineers, project managers, and senior staff from Saudi design and consultancy engineering firms actively involved in project management or AI implementation decisions. Data collection occurred over six weeks, with bi-weekly follow-up communications used to maximize response rates.

Qualitative Data Collection (Interviews):

Semi-structured interviews were conducted either in person or virtually, based on participant availability. Participants were selected purposefully to ensure diversity in roles, company size, and AI maturity levels. Interviews were audio-recorded with permission and transcribed for analysis.

3.6.4 Data Analysis Procedure

Quantitative Analysis: Conducted using SPSS v25 and SPSS AMOS through the following steps.

SPSS AMOS was chosen for its user-friendly graphical interface, support for Maximum Likelihood Estimation, and provision of comprehensive model fit indices (CFI, TLI, RMSEA), making it suitable for structural equation modeling. Its integration with SPSS also ensured greater accuracy in data handling and ease of analysis. SPSS AMOS represented the optimal balance between analytical capability, user accessibility, institutional availability, and time efficiency for this mixed-methods study.

Step 1: Data Preparation

- Data were entered into SPSS, coded, and screened for data-entry errors.
- Missing data were assessed; cases with more than 10% missing data were excluded.
- Descriptive statistics (means, standard deviations, ranges) were calculated for all variables.

Step 2: Reliability and Validity Testing

- Internal consistency was assessed using Cronbach's Alpha for each construct (acceptable threshold: $\alpha \geq 0.70$).
- Item-to-total correlations were examined to identify problematic items (criterion: $r \geq 0.30$).
- Validity coefficients were calculated for all measurement items.

Step 3: Preliminary Statistical Testing

- Descriptive statistics (frequencies, percentages, means, SDs) were reported for all variables.
- A Pearson correlation matrix was generated to assess bivariate relationships between variables.
- Simple and multiple linear regression analyses were conducted to test individual and combined effects of independent variables on outcomes.

Step 4: Structural Equation Modeling (SEM)

SEM was conducted using SPSS AMOS through the following two-step process.

Step 4a: Measurement Model (CFA)

- Confirmatory factor analysis was performed to validate the measurement model.
- All latent constructs (6 IVs, 1 mediating variable, 7 DVs) were specified with their respective observed indicators.
- Global fit indices were calculated and evaluated against thresholds:
 - $CFI \geq 0.90$ (acceptable), ≥ 0.95 (excellent)
 - $RMSEA \leq 0.08$ (acceptable), ≤ 0.06 (good)
 - $\chi^2/df \leq 3.0$ (acceptable), ≤ 2.0 (good)
- Standardized factor loadings were examined; items with loadings < 0.50 were considered for removal.
- Convergent validity was assessed via Average Variance Extracted ($AVE \geq 0.50$).

- Discriminant validity was tested using the Fornell-Larcker criterion and HTMT ratios (< 0.90).

Step 4b: Structural Model and Hypothesis Testing

- The structural model was estimated to test direct effects (H1: IVs → Outcomes; H3: Mediator → Outcomes).
- Standardized path coefficients were reported with standard errors and 95% confidence intervals.
- Hypothesis significance was determined at the $\alpha = 0.05$ level (two-tailed).
- R^2 values were calculated to assess the variance explained in each outcome variable.

Step 5: Mediation Analysis

Mediation analysis was conducted using path decomposition and bootstrap confidence intervals. For each indirect pathway (IV → AI-PM → DV):

- The direct effect was estimated.
- The indirect effect was calculated.
- 95% bias-corrected bootstrap confidence intervals were generated.
- The indirect effect was considered significant if the 95% CI did not include zero.
- The type of mediation (full, partial, or none) was determined for each pathway.
- The proportion of effect mediated was calculated to assess the relative contribution of the indirect pathway.

Qualitative Analysis: Conducted via thematic coding.

Step 1: Transcription and Data Preparation

- Interview audio recordings were transcribed verbatim using transcription software.
- Transcripts were manually reviewed for accuracy and corrected.
- Transcripts were imported into qualitative analysis software.

Step 2: Thematic Coding (Deductive–Inductive Hybrid Approach)

An a priori codebook was developed based on the theoretical framework:

- Codes for the six independent variables: Data Privacy, Resistance to Change, Cost, Infrastructure, Workforce, Ethics.
- Codes for the mediating variable (AI-based project management), with five sub-codes: planning, documentation, resource allocation, task prioritization, and communication.

- Codes for the seven dependent variables: Decision-Making, Quality, Data Accuracy, Data Analysis, Risk Identification, Time Efficiency, and Collaboration.

The first coding pass applied predefined codes to all interview data. The second coding pass identified inductive codes for themes not fitting the predefined framework, and these inductive codes were created to capture unexpected themes.

Step 3: Inter-Coder Reliability

A second independent coder coded 30% of interviews (n=3) using the finalized codebook. Cohen's Kappa was calculated, with $\kappa \geq 0.70$ considered acceptable. Disagreements between coders were resolved through discussion and codebook refinement.

Step 4: Theme Frequency and Interpretation

Code frequency was tabulated for each theme across interviews. The thematic saturation point was identified (the interview at which no new themes emerged). Representative quotes were selected for each theme to illustrate meaning and context, and relationships between codes were examined to identify patterns and hierarchies.

Triangulation (Integration of Quantitative and Qualitative Findings)

- Quantitative statistical pathways were mapped to qualitative themes.
- Convergence was assessed by comparing the significance of quantitative effects with the frequency and prominence of qualitative themes, and the direction of quantitative effects with the content of qualitative narratives.
- Where strong statistical relationships existed ($p < 0.05$), qualitative data were examined to provide contextual explanations and real-world examples.
- Discrepancy investigation: instances where statistical results appeared inconsistent with qualitative patterns were investigated and explored in depth.

3.6.5 Instrument Validation and Reliability

Content validity and practicality of the instruments were ensured through a combined expert review and pilot testing process. A panel of domain and methodology experts reviewed the draft questionnaire and interview guide, suggesting refinements to wording, clarity, and coverage of key constructs; their comments were incorporated before piloting. The questionnaire was then pilot-tested with 15 professionals from Saudi design and consultancy engineering firms, who completed the survey and provided structured feedback on clarity, flow, completion time, and any confusing or redundant items, which led to final adjustments before main data collection. Similarly, three pilot interviews were conducted using the draft interview protocol, and insights from these sessions

were used to refine question phrasing, ordering, and probing depth, resulting in the finalized interview guide for the qualitative phase.

3.7 Research Design and Statistical Processing

This section details the overall research design structure and the statistical methods employed in analyzing both quantitative and qualitative data. These procedures were selected to ensure methodological rigor and alignment with the study's objectives, research questions, and hypotheses.

3.7.1 Research Design

This study adopted a concurrent integration (simultaneous SEM and thematic coding) mixed-method research design, incorporating both statistical analysis and qualitative interpretation.

- **Quantitative Phase:** A structured questionnaire was distributed to professionals in Saudi design and consultancy engineering firms to collect data on the influencing factors (independent variables), the utilization of AI-based project management (mediating variable), and project outcomes (dependent variables).
- **Qualitative Phase:** Semi-structured interviews were conducted with a select group of industry experts to capture deeper contextual understanding, clarify survey trends, and provide interpretive insights.

This concurrent explanatory design was employed to:

- Identify and evaluate the key factors influencing the utilization of AI tools in project management within design and consultancy engineering projects.
- Analyze how AI-based project management mediates the relationship between influencing factors and project outcomes.
- Examine the direct influence of these factors on the outcomes of AI-based project management.
- Assess variations in AI utilization and outcomes across different organizational types, sizes, and participant demographics.
- Propose practical recommendations by combining statistical trends with real-world expert insights.

The research design followed a correlational approach, with mediation analysis techniques applied through SEM. This enabled the analysis of both direct and indirect relationships among variables, while qualitative findings offered deeper interpretive support.

3.7.2 Quantitative Data Analysis Procedure

To ensure rigorous quantitative analysis, data collected from the questionnaire were processed using the following statistical techniques:

1. Statistical Software and Analysis Tools:

- SPSS was used for descriptive statistics, correlations, and regression analyses.
- Simple and multiple linear regression were used to test direct effects of factors on project management outcomes.
- Pearson correlation analysis was conducted to examine bivariate relationships among variables.
- Significance level: $\alpha = 0.05$ (two-tailed tests).

2. Reliability and Validity Testing:

Reliability and validity were assessed following standard research-instrument evaluation practices (Tavakol & Dennick, 2011). Internal consistency was measured using Cronbach's Alpha, one of the most widely used indicators of the degree of interrelation among items measuring the same conceptual dimension.

- Cronbach's Alpha coefficients were calculated to assess the internal consistency of all constructs. The higher the value of Cronbach's Alpha (usually ≥ 0.70), the greater the indication that the items consistently measure the same construct.
 - **Independent Variables (6 factors):** Data Privacy and Security, Resistance to Change, Cost of AI Implementation, Compatibility with Existing Infrastructure, Workforce Development, and Ethical Considerations.
 - **Mediating Variable dimensions (5 dimensions):** Streamlining Processes, Resource Allocation, Task Prioritizing, Progress Reporting, and Communication.
 - **Dependent Variables (7 outcomes):** Decision-Making, Project Quality, Data Collection Accuracy, Data Analysis, Risk Identification Accuracy, Time Savings for Project Managers, and Effective Communication.
 - Threshold for acceptable reliability: $\alpha \geq 0.70$.
- The validity coefficient is an important statistical indicator used to estimate the accuracy of the research instrument in measuring the intended construct. This coefficient was calculated using the Pearson correlation coefficient, which measures the degree of the linear relationship between the total score of the instrument and the score of each item, or between two tests assumed to measure the same conceptual dimension.
 - Validity coefficients were determined using Pearson correlation (item-total correlations) to confirm that individual items accurately measured their intended constructs.

3. Descriptive Statistics Analysis:

Frequencies, percentages, means, and standard deviations were calculated for:

- All respondent demographics (position in organization, years of experience, organization size, AI familiarity level).
- All six independent variables.
- All five mediating-variable dimensions.
- All seven dependent variables.

This analysis provided a comprehensive profile of the sample and variable distributions.

4. Correlation Analysis:

A Pearson correlation matrix was computed to examine relationships among all study variables. Bivariate relationships were examined between:

- Independent Variables and the Mediating Variable
- The Mediating Variable and Dependent Variables
- Independent Variables and Dependent Variables

Statistical significance was assessed at $p < 0.05$ (two-tailed).

5. Regression Analysis:

To test the study's hypotheses, the following regression analyses were conducted:

- Simple linear regression was used to test each sub-hypothesis's individual factor effect.
- Multiple linear regression was used to test the combined effect of factors competing together within each hypothesis group.
- For H3, simple linear regression was used, as AI-based project management was the sole predictor of each outcome.
- For H4, structural equation modeling was used to test the complete mediation model, examining whether the influencing factors' effects on outcomes were transmitted through AI-based project management utilization. This followed established mediation protocols while delivering actionable insights for practitioners (Baron & Kenny, 1986; Hayes, 2018).

6. Structural Equation Modeling (SEM):

To comprehensively test mediation effects and the overall conceptual model, structural equation modeling was employed using AMOS statistical software.

- **Measurement Model Assessment:**
 - Confirmatory factor analysis (CFA) was conducted to validate the measurement model.
 - Factor loadings were examined to ensure convergent validity (target > 0.50).
 - Model fit indices were evaluated.

- **Structural Model Testing:**
 - Path coefficients were estimated to test direct relationships.
- **Mediation Analysis:**
 - Full mediation was tested to determine whether the mediating variable (AI-based project management) completely explained the relationship between influencing factors and project outcomes.
 - Partial mediation was assessed where the mediating variable only partially explained the relationship.
 - Statistical significance of indirect paths was evaluated ($p < 0.05$).
 - Total effects were decomposed into direct and indirect effects.

3.7.3 Qualitative Data Analysis Procedures

Data from the semi-structured expert interviews were analyzed through thematic coding, following this process:

1. Interview Data Collection:

- Semi-structured interviews were conducted with 10 expert participants from Saudi Arabia's design and consultancy engineering firms.
- Participants included individuals with direct involvement in AI-based project management decision-making and implementation.
- All interviews were audio-recorded with participant consent and subsequently transcribed verbatim for analysis.

2. Predefined Thematic Framework:

The qualitative analysis employed a structured thematic coding approach organized around 18 predefined themes that directly corresponded to the study's three variable categories:

Independent Variables (Factors Influencing AI Utilization) — 6 Themes:

1. Data Privacy and Security
2. Resistance to Change
3. Cost of AI Implementation
4. Compatibility with Existing Infrastructure
5. Workforce Development
6. Ethical Considerations

AI-Based Project Management Dimensions (Mediating Variable) — 5 Themes:

1. Streamlining Processes (scheduling, documentation, automation)
2. Resource Allocation
3. Task Prioritizing
4. Progress Reporting
5. Communication

Dependent Variables (Project Management Outcomes) — 7 Themes:

1. Decision-Making
2. Project Quality
3. Data Collection Accuracy
4. Enhancing Data Analysis
5. Risk Identification Accuracy
6. Time Saving
7. Effective Communication

3. Thematic Coding Process:

Each interview transcript was systematically coded against the 18 predefined themes. Coding documented:

- The primary theme(s) represented in each response
- The frequency of each theme's mention across all interviews
- Interview ID numbers where the theme appeared
- Recurring phrases and terminology associated with the theme
- Representative quotes exemplifying the theme
- Summary quotes synthesizing the theme across multiple responses

Thematic saturation was assessed during coding; data collection and analysis continued until no new substantive themes emerged from interviews.

4. Open-Ended Questionnaire Responses Analysis:

Responses to the five open-ended survey questions were analyzed using primarily deductive thematic coding, guided by the study's six independent variable constructs (data privacy/security, resistance to change, implementation cost, infrastructure compatibility, workforce development, ethical/regulatory considerations), while remaining open to emergent subthemes (e.g., data fragmentation, leadership support).

Coding was conducted by the principal researcher through iterative rounds, with codes cross-checked against the conceptual framework for consistency. As a single-coder analysis, formal inter-coder reliability (e.g., Cohen's Kappa) was not applicable; instead, trustworthiness was established via (1) framework alignment, (2) iterative refinement, and (3) triangulation with the quantitative SEM results (Section 4.10).

5. Qualitative Rigor Procedures:

- Predefined themes were reviewed and validated by academic experts to ensure alignment with study constructs.
- Thematic coding followed a transparent, systematic process aligned with the study's conceptual framework.
- Member checking was conducted where feasible to enhance the credibility of interpretation.

In addition to the predefined theme framework, the qualitative analysis followed a hybrid deductive–inductive approach. While transcripts were coded against the 18 predefined themes linked to the study variables, coders were also encouraged to create new inductive codes whenever interview segments did not fit the existing categories. Emergent themes were then reviewed for novelty, frequency, and relevance to the research questions; conceptually related ideas (for example, specific legacy-system integration issues or aspects of organizational risk culture) were incorporated as subthemes under the relevant predefined categories, whereas broader implementation issues (such as phased roll-out approaches or the role of executive sponsorship) were treated as supplementary contextual insights rather than additional core variables. This process ensured that the deductive framework provided structure without acting as a ceiling on discovery, allowing theoretically grounded but data-driven refinement of the thematic map.

3.7.4 Mixed-Method Integration and Triangulation Strategy

1. Concurrent Integration Approach:

Quantitative and qualitative data were analyzed concurrently (in parallel) and subsequently integrated through a systematic triangulation process to enhance the validity and richness of findings.

2. Triangulation Procedures:

- **Convergence Validation:**
 - Quantitative correlations and regression results were examined alongside qualitative thematic patterns.
 - Statistical relationships identified in regression analyses were compared with the frequency and strength of corresponding qualitative themes.
 - Where strong statistical relationships existed ($p < 0.05$), qualitative data were examined to provide contextual explanations and real-world examples.
- **Thematic-to-Quantitative Mapping:**
 - The frequency of qualitative theme mentions was cross-referenced against the magnitude of statistical coefficients.
 - Directional consistency was verified: positive statistical relationships aligned with enabling/facilitating themes, while negative relationships aligned with barrier themes.

- **Discrepancy Investigation:** Instances where statistical results appeared inconsistent with qualitative patterns were investigated and explored in depth.

3.7.5 Methodology summary

In summary, this study applied a robust mixed-method research design, combining structured quantitative data collection with in-depth qualitative interviews. This methodology aligned with the study's aim of examining the factors influencing the utilization of AI-based project management, the mediating role of AI in transforming project management practices, and the resulting project outcomes in design and consultancy engineering projects.

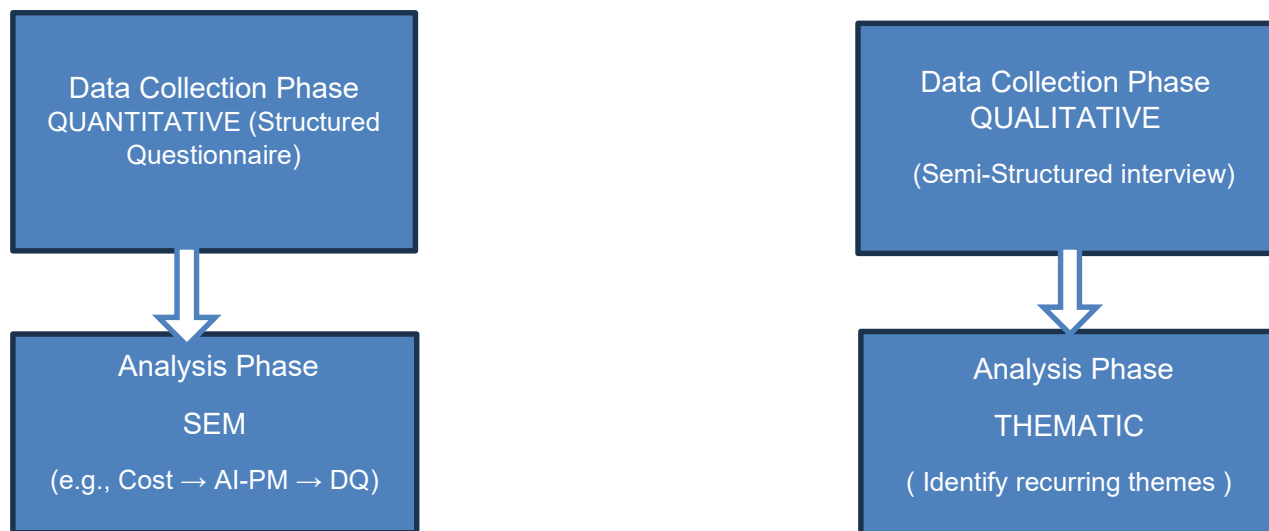
The quantitative phase involved the use of a structured questionnaire to collect statistically analyzable data from professionals across Saudi Arabia's design and consultancy sector. It allowed for the identification and measurement of relationships among the study's core variables: the influencing factors (independent variables), AI-based project management practices (mediating variable), and the outcomes of AI utilization (dependent variables). Structural equation modeling was applied to test both direct and indirect relationships, including mediation effects.

In parallel, the qualitative phase incorporated semi-structured interviews with selected experts to explore practical insights, contextual challenges, and real-world experiences related to AI-based project management. Thematic analysis of these interviews uncovered emergent themes aligned with the study variables and helped contextualize quantitative trends.

To ensure integration of insights, this study adopted a triangulation approach, whereby qualitative findings from expert interviews were used to interpret, validate, and enrich the patterns revealed through quantitative analysis. Thematic analysis of interview transcripts uncovered real-world examples, contextual explanations, and potential contradictions that helped explain statistical relationships or anomalies identified through SEM. This method reinforced the study's methodological rigor by ensuring that quantitative associations were not only empirically validated but also contextually grounded.

Visual Representation of Integration Strategy:

Figure 3 illustrates how the quantitative and qualitative methods worked together through SEM, thematic analysis, and triangulation.



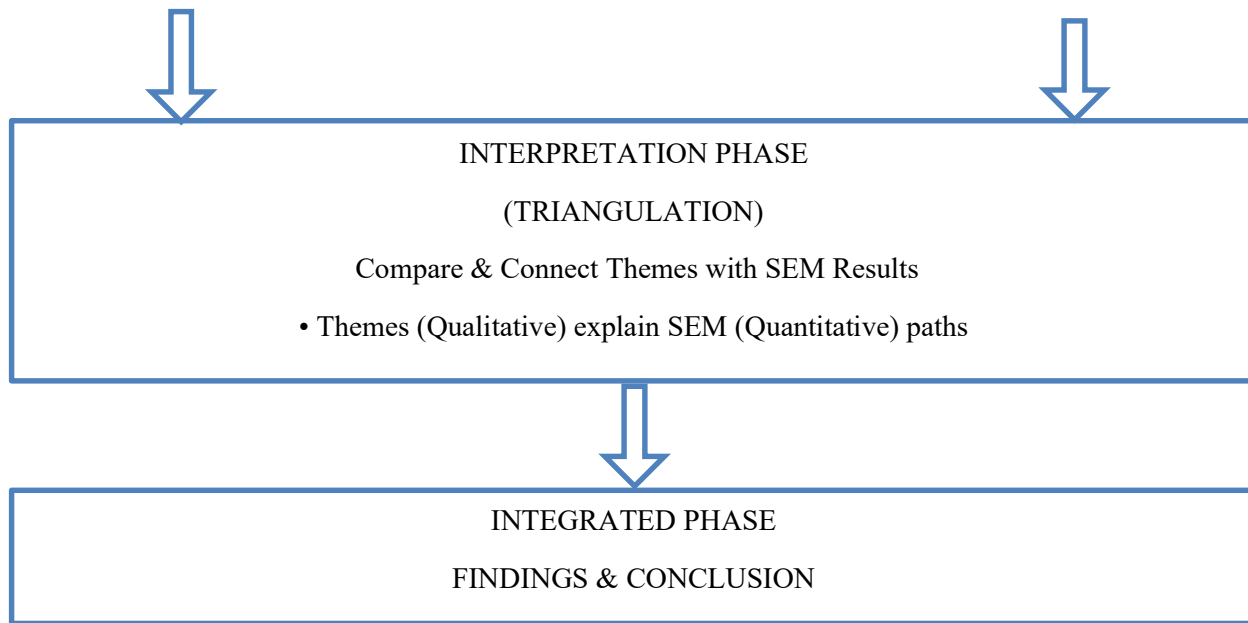


Figure (3) illustrates how the quantitative and qualitative methods work together through SEM, thematic analysis, and triangulation

The figure, developed by the researcher, shows how quantitative and qualitative methods were integrated through a triangulation approach to enhance interpretation and ensure robust findings. It walks through:

1. **Data Collection Phase:**
 - From the structured questionnaire (quantitative)
 - From semi-structured interviews (qualitative)
2. **Analysis Phase:**
 - SEM was applied to test relationships (e.g., Cost → AI-based PM → Decision-Making Quality)
 - Thematic analysis identified recurring themes from interview transcripts (e.g., "Cost is a major barrier")
3. **Interpretation Phase (Triangulation):**
 - Findings from interviews were connected with SEM results to explain, support, or challenge quantitative relationships.
4. **Integrated Conclusion:**
 - A richer understanding was achieved by combining numbers (how much) with narratives (why), resulting in conclusions that were both statistically validated and contextually meaningful.

This integration enhanced both the methodological rigor and practical relevance of the study by combining statistical evidence with expert-driven interpretation. As a result, the study's findings and recommendations are both theoretically robust and grounded in the lived realities of AI utilization in the Saudi design and consultancy engineering sector.

3.8 Chapter 3 Summary

Chapter 3 detailed the concurrent mixed-methods approach, with $n=103$ questionnaire respondents (G*Power validated, power = 0.95) and 10 saturation interviews conducted with Saudi design/consultancy professionals (project directors, managers, engineers). Instruments included a five-point Likert questionnaire measuring independent variables, the AI-based project management mediator, and project management outcomes, plus demographic and open-ended questions, validated via pilot testing (Cronbach's $\alpha > 0.70$) and expert review. Analysis employed SPSS descriptive statistics, correlations, and regressions, along with AMOS two-step SEM (CFA validation, then path/bootstrap mediation) and thematic analysis, with Figure 3 illustrating the triangulation integrating SEM paths and qualitative themes. The sample met SEM requirements ($n=103$ exceeds the 10–20 cases-per-parameter guideline) and qualitative saturation was achieved within the planned 10–12 interview range, with ethical procedures and mixed-methods challenges addressed through triangulation protocols. This chapter established the methodological foundation for hypothesis testing per H1–H4 in Chapter 4.

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CHAPTER 4

4 Study Results and Hypothesis Testing

4.1 Introduction

This chapter presents the comprehensive results from both quantitative and qualitative data analyses, organized to align with the methodological procedures outlined in Chapter 3. The chapter integrates findings from 103 quantitative survey responses and 10 semi-structured interviews, employing a triangulation strategy to validate and contextualize statistical relationships through qualitative narratives. Results are presented sequentially across reliability and validity testing, demographic profiling, descriptive statistics, correlation analysis, hypothesis testing via regression and SEM, and qualitative thematic findings.

After data were collected it was revised, coded, and fed to statistical software IBM SPSS version 25. All statistical analysis was done using two-tailed tests and an alpha error of 0.05. A P-value less than or equal to 0.05 was considered to be statistically significant.

Detailed statistical tables (full reliability, validity, and regression outputs) are provided in Appendix C; this chapter presents the key results needed for hypothesis testing and interpretation.

4.2 Reliability and Validity of Research Instruments

4.2.1 Reliability Analysis (Cronbach's Alpha)

Reliability testing was conducted using Cronbach's Alpha to assess internal consistency across all constructs. Results demonstrated strong reliability across all three variable categories: All Cronbach's Alpha values exceeded the 0.70 threshold, confirming that the questionnaire reliably measured the intended constructs and was suitable for hypothesis testing.

Detailed item-level validity and stability coefficients for all constructs (Tables 2, 3, and 4) are provided in Appendix C. Table 5 in the main text summarizes the consolidated Cronbach's Alpha reliability results for pilot and main studies across all variable groups.

Table (5): Reliability Analysis (Cronbach's Alpha) for Pilot and Main Study Variables

Variables	Stability Coefficient (Cronbach's alpha)	
	Pilot study	Main study
Factors Influencing AI utilization	0.879	0.815
AI-Based Project Management	0.886	0.918
Project Management Outcomes	0.905	0.922

Note. Cronbach's alpha for "Factors Influencing AI" decreased from 0.879 in the pilot to 0.815 in the main study; both values are above the 0.70 threshold and indicate acceptable to good internal consistency. This minor reduction is

explained by the larger and more heterogeneous main sample (n = 103) compared with the small, homogeneous pilot group (n = 15), which naturally introduced greater response variability without any change to the underlying items.

Table (5) presents Cronbach's Alpha values for both the pilot and main studies across key variables. All values exceed 0.7, indicating high reliability of the measurement instruments for: (Factors Influencing AI Utilization, AI-Based Project Management, Project Management Outcomes) These results confirm that the research instruments are reliable and suitable for subsequent statistical analysis.

Pilot alphas (n=15) all exceeded 0.70 with no low-performing items requiring revision/deletion, only minor wording clarifications from feedback. The instrument proceeded directly to main study without re-piloting as pilot results validated reliability and structure.

4.3 Respondent Demographic Profile

The study sample comprised n = 103 professionals from Saudi Arabia's design and consultancy engineering firms.

Demographic distribution revealed:

4.3.1 Demographic Profile: Contextual Interpretation for Saudi Engineering Sector

The demographic characteristics of the study sample reflect important features of the Saudi design and consultancy engineering sector and have implications for findings interpretation and generalizability.

The demographic profile (Tables 6-10) with full distributions in Appendix C, reveals a senior, experienced sample primarily from medium/large Saudi design/consultancy firms. Table (11) in the main text summarizes key demographic characteristics supporting the contextual interpretation in section 4.3.6

Table (11): Respondent Profile Summary

Demographic Characteristic	Key Findings	Percent Distribution
Position	Mixed hierarchical levels, weighted toward frontline roles	18% Top Management, 17% Project Managers, 32% Project Engineers, 25% Engineers, 8% Other
Experience	Highly experienced professionals	58% >10 years, 21% 7-10 years
Organization Size	Medium/Large firms predominate	47% Medium (50–249 employees), 45% Large ($\geq$ 250 employees)
AI Familiarity	Moderate AI exposure	44% "Moderate", 28% "High"
AI Tools Used	Basic tools most common	62% Excel AI + basic PMIS, 22% Advanced AI

Table (11) consolidates key demographic characteristics, with full distributions in Appendix C. This experienced cohort from established firms informs AI-PM utilization analysis while highlighting generalizability considerations.

This demographic profile summary (**Table 11**) fulfills Objective 4 by describing the distribution of AI utilization and outcomes across organizational characteristics, with full distributions in Appendix C.

High Experience Level (58.25% with >10 years of experience):

The predominance of highly experienced practitioners (60 of 103 respondents with ≥ 10 years' experience) shows a sample well-suited to providing nuanced insights into AI utilization challenges, as senior professionals represent key decision-makers influencing strategy and implementation.

Medium-Large Firm Dominance (91.26% from medium/large firms):

91.26% of sample came from medium (50–249 employees) or large (≥ 250 employees) firms, while only 8.74% from small firms (< 50 employees). This concentration reflects:

- The study primarily captures conditions in established firms with greater financial capacity for AI investment.
- The sample is predominantly composed of medium and large organizations, while very small firms are comparatively underrepresented. Consequently, the quantitative results primarily reflect the conditions of medium and large design and consultancy firms. Consequently, caution is advised when generalizing the results to very small firms, which may face different structural, financial, and technological constraints in utilizing AI-based project management.

Mixed Organizational Levels (32% Project Engineers, 25% Engineers, 17% Project Managers, 18% Top Management, 8% Other):

Distribution across hierarchical levels provides triangulation of perspectives:

- Project managers (17%), project engineers (32%), and engineers (25%) together represent frontline practitioners experiencing AI impact directly.
- Top management (18%) represents the strategic decision-making perspective.
- This mix captures diverse viewpoints while acknowledging that implementation-level perspectives (project managers, project engineers, and engineers) are weighted more heavily.

Moderate AI Familiarity (72% moderately to highly familiar; 27% somewhat familiar):

The generally positive AI familiarity distribution is consistent with:

- Saudi Arabia's strategic focus (Vision 2030) on digital transformation, and study conducted during period of increased AI awareness post-ChatGPT (2023).
- Selection bias: Respondents have above-average AI familiarity
- Implication: Findings represent "early/mid-majority" perspectives.

Sectoral Context - Design & Consultancy Specialization:

All respondents came from design and consultancy engineering firms (vs. construction, operations, or other sectors). This specialization is intentional (research scope) but limits generalizability:

- Design/consultancy sector emphasizes data analysis, innovation, and client-specific solutions contexts where AI utilization is particularly relevant
- Construction and operations sectors may face different AI barriers (physical asset management, safety-critical operations)
- Findings strongly represent design/consultancy sectors; generalization to other engineering sectors should be cautious.

Qualitative Validation: Interviewees confirmed this demographic profile, with experienced professionals (averaging 12+ years) and medium-to-large firms representing the most engaged segment, consistent with the quantitative distribution.

Overall Demographic Assessment:

The sample represents experienced practitioners at medium-large design/consultancy firms with moderate-to-high AI familiarity, capturing the perspective of organizations actively engaged in digital transformation. This sample is well-suited to studying AI utilization determinants and outcomes but may overrepresent established firms and experienced personnel, potentially underrepresenting barriers faced by smaller firms, newer consultancies, or AI-skeptical practitioners.

Respondents' Perceptions of Study Variables:

Following the demographic profile, Tables 12-14 present respondents' perceptions of the study's key constructs: factors influencing AI utilization (**Table 12**), AI-based project management practices (**Table 13**), and project management outcomes (**Table 14**).

Detailed item-level distributions for the study's key constructs; factors influencing AI utilization (Table 12), AI-based project management practices (Table 13), and project management outcomes (Table 14); are provided in **Appendix C**. These tables reveal consistently high mean scores across all items (3.60–4.26), with mean score percentages >70–85%, confirming strong positive perceptions of AI's role in project management. The following **Table 15** provides the summary of Tables 12-14;

Table 15: Consolidated Perceptions of AI Factors, Practices, and Outcomes (Summary of Tables 12-14)

Construct (Table)	Mean $\pm$ SD Range	Median	Top 3 Items (%Agree/Strongly Agree)	Lowest (%Agree/Strongly Agree)
AI Factors (12)	3.60 $\pm$ 1.09 - 4.07 $\pm$ 0.84	4	Training limits (81%), Ethics risks (81%), Data security challenges (75%)	Infra compatibility (72%)
AI Practices (13)	3.91 $\pm$ 0.98 - 4.19 $\pm$ 0.81	4	Reporting (84%), Comm platforms (82%), Task coord (80%)	Resource alloc (78%)
Outcomes (14)	3.90 $\pm$ 0.90 - 4.26 $\pm$ 0.70	4	Data insights (85%), Time savings (85%), Error reduction (85%)	Team collab (79%)

In summary, all 103 respondents strongly endorse AI's benefits ($\geq 78\%$ agreement across constructs, medians=4.0). Highest agreement centers on time savings (85%), data insights (85%), and error reduction (85%). Primary barriers remain infrastructure compatibility (72%) and training deficiencies (81%). These findings indicate Saudi engineering firms recognize AI's potential but require technical infrastructure and workforce upskilling for optimal implementation.

4.4 Descriptive Statistics of Variables

Table (16) presents the summary of the composite descriptive statistics for the three primary variable groups in this study: independent variables (IVs), the mediating variable (MV), and dependent variables (DVs). The IVs, representing organizational and technical factors influencing AI utilization, demonstrate a strong overall readiness, reflected in a composite mean score of 45.96 (SD = 6.54) and an approximately normal distribution (skewness = 0.14; kurtosis = -0.50). The MV, capturing AI-based project management adoption, shows a high composite mean of 40.19 (SD = 6.99) with a pronounced negative skew (-1.08) and moderate leptokurtic form (1.12), indicating a clustering of higher adoption levels among respondents. Similarly, the DVs, which measure various aspects of project management outcomes, record the highest composite mean of 57.67 (SD = 8.22), also demonstrating negative skew (-1.04) and leptokurtic kurtosis (1.98), suggesting consistently strong positive perceptions of AI's impact on project success. Importantly, all skewness and kurtosis values fall within the acceptable range of -2 to +2, confirming that the data meet the criteria for approximate univariate normality. Accordingly, the use of parametric statistical tests is justified in the subsequent analysis (George & Mallery, 2010).

The composite distributional results are summarized in Table 16. Additional non-normality diagnostics and bootstrap-stability information are provided in Appendix C.

4.4.1 Independent Variables (Factors Influencing AI Utilization)

Detailed descriptive statistics for each independent variable are provided in Appendix C, Table 17

4.4.2 Mediating Variables (AI-Based Project Management)

Table 18 summarizes the descriptive statistics for the AI-based project-management dimensions. Detailed values and qualitative supporting evidence are provided in Appendix

4.4.3 Dependent Variables (Project Management Outcomes)

Table 19 presents the composite descriptive statistics for project-management outcomes. Detailed item-level results and qualitative corroboration are provided in Appendix C.

4.4.4 Open-ended questions

The open-ended responses identified recurring challenges related to data quality and integration, infrastructure compatibility, workforce skills and training, cost, resistance to change, data privacy and security, and ethical governance. The responses were coded thematically and correspond closely with the quantitative constructs used as independent variables, reinforcing the conceptual coherence of the study design. Table 25 summarizes the frequencies of the principal challenge themes, while the full open-ended responses and detailed coding results are provided in Appendix C, Tables 20–24.

4.5 Correlation Analysis (Pearson Correlation Matrix)

Pearson's correlation coefficient was used to assess the direction and strength of the linear associations among the study variables. The coefficient ranges from -1 to $+1$, with positive values indicating that higher values of one variable are associated with higher values of another. Because correlation measures association rather than causation, the results are interpreted as preliminary evidence of relationships and are examined further through regression analysis and structural equation modeling.

Table (26) presents a **correlation and regression summary** highlighting the key relationships among independent variables (IVs), the mediating variable (AI-based project management, MV), and dependent variables (DVs). The IVs show moderate positive correlations with the MV, indicating that better organizational and technical readiness is associated with higher AI adoption. The MV exhibits a very strong positive correlation and regression effect on DVs, demonstrating its critical role in improving project outcomes. Although IVs also directly correlate positively with DVs, these effects are weaker than the mediated path through AI-based project management, confirming partial mediation.

Table (26): Correlation and Regression Summary for Key Variable Relationships

Relationship	r	p-value	Interpretation
IVs → MV (AI-PM)			Positive, significant associations indicating stronger AI-PM with better enablers
Workforce → AI-PM	0.527	< 0.01	Strongest predictor
Infrastructure → AI-PM	0.521	< 0.01	Strong
Cost → AI-PM	0.325	< 0.01	Moderate
MV → DVs			Very strong positive effect, confirming AI-PM greatly improves project outcomes
AI-PM → Project Outcomes	0.775	< 0.001	Very strong mediation effect
AI-PM → Decision-Making	0.716	< 0.001	Strong
IVs → DVs (Direct)			Moderate direct positive effects, partially mediated via AI-PM
Workforce → Outcomes	0.494	< 0.05	Moderate (partial mediation)
Infrastructure → Outcomes	0.463	< 0.001	Moderate

Note: The full 18-variable correlation matrix is provided in **Table (27) in Appendix C** for readers who require detailed coefficients. All relationships above are statistically significant, with only minor non-significant coefficients in the full matrix.

The results presented in **Table (26)**, supported by the full correlation matrix in **Table (27) in Appendix C**, reveal statistically significant relationships among the independent variables (factors influencing AI utilization), the mediating variable (AI-based project management), and the dependent variables (project management outcomes). **First**, correlations between the independent variables and AI-based project management are all positive and statistically significant (r ranging from 0.325 to 0.527, $p < 0.01$), indicating that improvements in organizational and technical enablers are associated with greater and more effective AI-PM utilization. **Second**, the strong positive correlation between AI-based project management and project management outcomes ($r = 0.775$, $p = 0.000$) demonstrates that effective AI-PM substantially contributes to improved project success. **Finally**, direct relationships between independent variables and outcomes are also positive and significant ($r = 0.275$ to 0.494), but weaker than the mediated path, supporting a partial mediation role for AI-based project management.

In summary, the findings highlight a coherent relational pattern where organizational and technical factors positively influence AI-based project management, which in turn significantly enhances project outcomes. This supports the conceptual framework of the study, confirming both the direct and indirect effects of the independent variables on project performance through the mediating role of AI-based project management.

4.5.1 Multicollinearity Assessment

VIF values remained below the accepted threshold, indicating that multicollinearity was not a serious concern. Detailed VIF values and the full correlation matrix are provided in Appendix C.

4.6 Structural Equation Modeling (SEM): Model Specification and Technical Analysis

The SEM mediation analysis was conducted in two phases: an initial model and a refined modified model. The initial and modified structural equation models, together with their detailed fit indices and parameter estimates, are provided in Appendix C, Figures 9 and 10 and Tables 28–30.

The initial structural model reflected the conceptual framework by specifying direct paths from the six influencing factors to AI-based project management and from AI-based project management to project outcomes. After estimating the initial model, modification indices and standardized residuals were examined to identify potential areas of misfit. Modifications were made only when theoretically justifiable, and the number of modifications was deliberately minimized to reduce the risk of capitalization on chance and to preserve consistency with the original conceptual logic.

The modified model showed an improved fit compared with the initial model and provided the preferred representation of the proposed mediation structure. The detailed model-fit statistics, path coefficients, factor loadings, and measurement-model outputs are reported in Appendix C.

4.7 Hypothesis Testing Results

Detailed regression outputs and technical analyses supporting H1–H3 are provided in Appendix C. This section presents the consolidated hypothesis results, mediation interpretation, and integrated findings.

4.7.1 Summary of Hypothesis Testing Results

This section presents comprehensive results of hypothesis testing across four hypothesis groups: H1 (organizational factors → outcomes), H2(organizational factors → AI-PM adoption), H3 (AI-PM → outcomes), and H4(mediation model). Results demonstrate 55% overall hypothesis support (11 of 20 hypotheses), with strong support for the overall H1 and H2models (main effects) and perfect support for H3 and H4. For H1 and H2, simple regression models confirm that all six factors identified through the literature review and the researcher's professional experience are individually significant, while the final multiple-regression models show that workforce development emerges as the single most robust and consistent predictor across both relationships, with infrastructure compatibility remaining significant for H2 (AI-PM adoption) specifically. The consolidated hypothesis results are presented across four groups: H1, H2, H3, and H4.

4.7.1.1 Hypothesis Support Criteria;

To standardize interpretation across all hypothesis tables, the following criterial will be applied:

SUPPORTED: $p < 0.05$, STRONGLY SUPPORTED: $p < 0.01$, VERY STRONGLY

SUPPORTED: $p < 0.001$ AND $B > 2.0$ (large effect size)

4.7.1.2 H1 INTERPRETATION SUMMARY

Hypothesis H1 proposes that some of the organizational and technical factors identified through the literature review and the researcher's professional experience — while other influencing conditions may exist beyond those examined here — influence project outcomes. Table 64 summarizes the simple linear regression results for the overall H1 model and its six sub-hypotheses. The overall model was statistically significant and explained 23.5% of the variance in project outcomes ($R = 0.485$, $R^2 = 0.235$, $F = 30.989$, $p < .001$). Accordingly, the main H1 hypothesis was supported in the simple regression analysis.

The six sub-hypotheses were also statistically significant in the individual simple regression models. However, when all six factors were entered progressively into a stepwise multiple-regression model, only workforce development retained statistical significance in the final step ($p = .009$); infrastructure compatibility, though significant at an earlier step of the model, did not retain independent significance once workforce development and ethical considerations were added. This pattern, consistent with Bodea et al. (2020) and Müller et al. (2024), suggests that workforce capability functions as the more direct determinant of project outcomes, while infrastructure operates primarily as an enabling condition. Detailed regression outputs are provided in Appendix C, while the effect-size ranking is presented in Appendix C, Table 65.

Table (64) : H1 Direct Effects (IVs $\rightarrow$ Project Outcomes)

#	Hypothesis	Analysis Type	R	R ²	B (Constant)	B ₁ (Coefficient)	F-test	F p-value	t-test	t p-value	Result
H1	Main Effect: All 6 IVs → Project Outcomes	Simple Linear Regression	0.485	0.235	29.69	0.61	30.989	0.000*	5.567	0.000*	STRONGLY SUPPORTED
H1A	Data Privacy & Security → Project Outcomes	Simple Linear Regression	0.275	0.076	46.37	1.52	8.291	0.005*	2.88	0.005*	SUPPORTED
H1B	Resistance to Change → Project Outcomes	Simple Linear Regression	0.345	0.119	43.59	1.82	13.601	0.000*	3.688	0.000*	STRONGLY SUPPORTED
H1C	Cost of AI Implementation → Project Outcomes	Simple Linear Regression	0.273	0.074	47.92	1.28	8.123	0.005*	2.85	0.005*	SUPPORTED
H1D	Infrastructure Compatibility → Project Outcomes	Simple Linear Regression	0.463	0.214	37.15	2.75	27.518	0.000*	5.246	0.000*	VERY STRONGLY SUPPORTED
H1E	Workforce Development → Project Outcomes	Simple Linear Regression	0.494	0.244	35.38	2.91	32.573	0.000*	5.707	0.000*	VERY STRONGLY SUPPORTED
H1F	Ethical Considerations → Project Outcomes	Simple Linear Regression	0.314	0.099	41.95	1.97	11.075	0.001*	3.328	0.001*	STRONGLY SUPPORTED

Notes: All H1A–H1F sub-hypotheses were statistically significant in the individual simple regression models at $p < .05$. The combined multiple-regression model produced a more selective pattern, with infrastructure compatibility and workforce development retaining independent statistical significance.

Strategic Implication:

The H1 results establish direct associations between the influencing factors and project outcomes. The next hypothesis group examines whether these factors also predict AI-based project-management utilization, while H4 later tests whether AI-based project management mediates their relationship with project outcomes.

Sub-hypothesis results: H1A–H1F

All six H1 sub-hypotheses were supported in the individual simple regression analyses. The detailed effect-size ranking and combined-model comparison are provided in Appendix C, Table 65.

Strategic Implication:

The H1 results establish direct associations between the influencing factors and project outcomes. The next hypothesis group examines whether these factors also predict AI-based project-management utilization, while H4 later tests whether AI-based project management mediates their relationship with project outcomes.

4.7.1.3 H2 INTERPRETATION SUMMARY

Hypothesis H2 examines whether the organizational and technical factors influence the utilization of AI-based project-management practices. Table 66 summarizes the simple linear regression results for the overall H2 model and its six sub-hypotheses. The overall model was statistically

significant and explained 25.2% of the variance in AI-based project-management utilization ($R = 0.502$, $R^2 = 0.252$, $F = 33.976$, $p < .001$). Accordingly, the main H2 hypothesis was supported in the simple regression analysis.

The six influencing factors were examined individually in the simple regression models. Most sub-hypotheses were statistically significant, while data privacy and security was marginally non-significant ($p = .053$). When all six factors were entered simultaneously in the multiple-regression model, infrastructure compatibility and workforce development remained the strongest statistically significant independent predictors. Detailed regression outputs are provided in Appendix C, while the effect-size ranking and comparison of simple- and multiple-regression results are presented in Appendix C, Table 67.

Table (66) : H2 Direct Effects (IVs → AI-PM Adoption

#	Hypothesis	Analysis Type	R	R ²	B (Constant)	B ₁ (Coefficient)	F-test	F p-value	t-test	t p-value	Result
H2	Main Effect: All 6 IVs → AI-Based PM	Simple Linear Regression	0.502	0.252	15.54	0.54	33.98	0.000*	5.829	0.000*	STRONGLY SUPPORTED
H2A	Data Privacy & Security → AI-Based PM	Simple Linear Regression	0.191	0.037	33.51	0.9	3.832	0.053	1.957	0.053	MARGINALLY INSIGNIFICANT
H2B	Resistance to Change → AI-Based PM	Simple Linear Regression	0.341	0.116	28.36	1.53	13.25	0.000*	3.64	0.000*	STRONGLY SUPPORTED
H2C	Cost of AI Implementation → AI-Based PM	Simple Linear Regression	0.325	0.105	30.32	1.29	11.89	0.001*	3.448	0.001*	SUPPORTED
H2D	Infrastructure Compatibility → AI-Based PM	Simple Linear Regression	0.521	0.271	20.54	2.63	37.6	0.000*	6.132	0.000*	VERY STRONGLY SUPPORTED
H2E	Workforce Development → AI-Based PM	Simple Linear Regression	0.527	0.278	19.95	2.64	38.83	0.000*	6.231	0.000*	VERY STRONGLY SUPPORTED

H2F	Ethical Considerations → AI-Based PM	Simple Linear Regression	0.335	0.112	25.95	1.79	12.74	0.001*	3.57	0.001*	SUPPORTED
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Note: Most sub-hypotheses were statistically significant in the individual simple regression models at $p < .05$. Data privacy and security was marginally non-significant ($p = .053$). In the combined multiple-regression model, infrastructure compatibility ($p = .013$) and workforce development ($p = .007$) remained statistically significant.

H2 Sub-hypothesis summary

The H2 sub-hypotheses were assessed in the individual simple regression models. The detailed coefficient estimates, multiple-regression results, and effect-size ranking are provided in Appendix C, Table 67. The combined model showed that infrastructure compatibility and workforce development made the strongest independent contributions to AI-based project-management utilization

Strategic Implication:

The H2 results establish that organizational readiness, particularly infrastructure compatibility and workforce development, is associated with AI-based project-management utilization. The next hypothesis group examines whether AI-based project-management utilization translates into improved project outcomes across seven outcome dimensions.

4.7.1.4 H3 INTERPRETATION SUMMARY

Hypothesis H3 examines whether AI-based project management influences project-management outcomes. Table 68 summarizes the simple linear regression results for the overall H3 model and its seven outcome-specific sub-hypotheses: decision-making effectiveness, project quality, data collection accuracy, data analysis and insight generation, risk identification accuracy, time efficiency, and communication and collaboration.

The overall H3 model was statistically significant and explained 60.0% of the variance in project-management outcomes ($R = 0.775$, $R^2 = 0.600$, $F = 151.592$, $p < .001$). Accordingly, the main H3 hypothesis was very strongly supported.

Table (68) H3 Direct Effects (AI-PM → Project Outcomes)

#	Hypothesis	Analysis Type	R	R ²	B (Constant)	B ₁ (Coefficient)	F-test	F p-value	t-test	t p-value	Result
H3	Main Effect: AI-PM → All Project Outcomes	Simple Linear Regression	0.775	0.6	21.08	0.91	151.6	0.000*	12.31	0.000*	VERY STRONGLY SUPPORTED
H3A	AI-PM → Decision-Making Effectiveness	Simple Linear Regression	0.716	0.5	1.35	0.17	106.2	0.000*	10.31	0.000*	VERY STRONGLY SUPPORTED

H3B	AI-PM → Project Quality	Simple Linear Regression	0.675	0.5	2.06	0.15	84.53	0.000*	9.194	0.000*	VERY STRONGLY SUPPORTED
H3C	AI-PM → Data Collection Accuracy	Simple Linear Regression	0.566	0.3	3.62	0.12	47.71	0.000*	6.907	0.000*	STRONGLY SUPPORTED
H3D	AI-PM → Data Analysis & Insight Generation	Simple Linear Regression	0.495	0.2	4.53	0.1	32.69	0.000*	5.718	0.000*	SUPPORTED
H3E	AI-PM → Risk Identification Accuracy	Simple Linear Regression	0.677	0.5	2.2	0.15	85.52	0.000*	9.248	0.000*	VERY STRONGLY SUPPORTED
H3F	AI-PM → Time Efficiency (Reduces Time for PMs)	Simple Linear Regression	0.492	0.2	4.98	0.09	32.21	0.000*	5.675	0.000*	SUPPORTED
H3G	AI-PM → Communication & Collaboration	Simple Linear Regression	0.629	0.4	2.34	0.14	66.24	0.000*	8.139	0.000*	VERY STRONGLY SUPPORTED

Note: All H3A–H3G sub-hypotheses were statistically significant in the individual simple regression models at $p < .001$. Multiple-regression analyses of the individual AI-PM dimensions produced varying effect sizes across the outcome dimensions

H3 sub-hypothesis results

All seven H3 sub-hypotheses were supported in the individual simple regression analyses. Decision-making showed the strongest relationship with AI-based project management ($R = 0.716$, $R^2 = 0.513$), followed by risk identification accuracy ($R = 0.677$, $R^2 = 0.459$) and project quality ($R = 0.675$, $R^2 = 0.456$). Time efficiency showed the weakest relationship among the seven outcomes, but the relationship remained statistically significant ($R = 0.492$, $R^2 = 0.242$, $p < .001$).

The detailed H3 regression outputs and effect-size ranking are provided in Appendix C, Table 69 and the associated H3 regression tables.

Strategic Implication:

The H3 results demonstrate that AI-based project management is strongly associated with improvements across all seven project-management outcomes. H4 therefore examines whether AI-based project management mediates the relationship between the influencing factors and project outcomes.

4.7.1.5 H4 Mediation Analysis Summary

Hypothesis H4 proposes that AI-based project management mediates the relationship between influencing factors and project outcomes in design and consultancy engineering projects. This

mediation analysis provides the final synthesis of the proposed theoretical model by testing whether organizational influencing factors contribute to improved project outcomes directly, indirectly through AI-PM utilization, or through both pathways.

Table (70) presents the complete mediation analysis by comparing the direct, indirect, and total effects. It also indicates the proportion of the relationship that operates through AI-PM utilization.

Table (70) Complete H4 Mediation Analysis Summary

H4 Mediation Analysis Summary									
#	Hypothesis	Analysis Type	Pathway	Direct Effect	Indirect Effect	Total Effect	Mediation %	P-value	Result
H4	Mediation: IVs → AI-PM → Outcomes	SEM Mediation	Full Model	0.125 (NS)	Significant	1.036**	88%	0.455 / <0.001	FULL MEDIATION SUPPORTED

Note;

Mediation Calculation: Indirect effect ($a \times b$) = 0.889 (IV → AI-PM) $\times$ 1.036 (AI-PM → Outcomes) = 0.921

Total effect (c) = Direct (0.125) + Indirect (0.921) = 1.046

Proportion mediated = $0.921 / 1.046 = 88\%$

H4 Sub-hypothesis Results: Full Mediation Supported

The H4 mediation hypothesis examined whether the effects of organizational influencing factors on project outcomes operate through AI-PM utilization. The results support full mediation in the tested model: the paths from influencing factors to AI-PM and from AI-PM to project outcomes were statistically significant, whereas the direct path from influencing factors to project outcomes was not statistically significant.

The modified SEM model reveals three critical findings:

- **Path A** (Influencing Factors → AI-PM): 0.889 ($p < .001$) — Organizational factors strongly drive AI-PM utilization.
- **Path B** (AI-PM → Project Outcomes): 1.036 ($p < .001$) — AI-PM very strongly predicts outcomes
- **Path C'** (Direct: Influencing Factors → Outcomes): 0.125 ($p = .455$, NOT SIGNIFICANT), The direct effect is negligible and non-significant

This pattern supports full mediation because the indirect pathway through AI-PM was statistically significant, while the direct pathway from influencing factors to project outcomes was not statistically significant. The findings indicate that organizational factors contribute to

project outcomes primarily by enabling the adoption and utilization of AI-based project management.

Detailed fit indices and path coefficients for the initial and modified SEM models are presented in Appendix C under “**H4 SEM Model Comparison: Initial vs Modified.**”

MODEL FIT ASSESSMENT: Initial vs Modified

The transition from the initial to the modified structural equation model represented a refinement of the model specification to better represent the observed data structure. **Table (71)** compares the principal fit indices of the initial and modified SEM models.

Table (71) MODEL FIT Comparison: Initial vs Modified:

MODEL FIT Comparison: Initial vs Modified				
Index	Threshold	Initial	Modified	Status
CMIN/DF	≤2.0 (good), ≤3.0 (accept)	2.322	1.779	GOOD (improved)
CFI	≥0.90 (excellent), ≥0.85 (accept)	0.851	0.917	EXCELLENT (exceeded threshold)
GFI	≥0.90	0.751	0.816	Approaching (improved)
AGFI	≥0.80	0.68	0.75	Approaching (improved)
NFI	≥0.90	0.768	0.832	Improved but below
RMSEA	≤0.06 (good), ≤0.08 (accept)	0.114	0.087	BORDERLINE ACCEPT (much improved)
CMIN	Lower is better	308.816	224.128	IMPROVED (27% reduction)

Overall, the modified SEM model demonstrated improved and acceptable fit and was therefore used as the preferred specification for evaluating the mediation hypothesis.

4.7.1.5.1 Overall Model Quality Assessment:

The reliability and validity assessment of the initial and modified measurement models, including factor loadings, composite reliability, average variance extracted, and square roots of AVE, is presented in Appendix C under “H4 SEM MODEL COMPARISON” The results support the adequacy of the measurement model for the subsequent structural analysis.

4.7.1.5.2 H4 CONCLUSION: FULL MEDIATION MODEL

H4, the mediation hypothesis, is strongly supported. AI-based project management fully mediates the relationship between organizational influencing factors and project outcomes in the tested model. The indirect pathway through AI-PM was statistically significant, whereas the direct pathway from influencing factors to project outcomes was not statistically significant.

Strategic Insight

The findings indicate that organizational factors contribute to project success primarily by enabling the adoption and utilization of AI-based project management. Infrastructure, workforce capability, and related organizational conditions remain important, but their contribution to project outcomes depends substantially on the effective implementation of AI-PM.

The cumulative findings across H1, H2, H3, and H4 provide an integrated framework for understanding the relationships among organizational factors, AI-PM utilization, and project outcomes. The subsequent comparative tables synthesize these findings and highlight the relative importance of the different pathways.

4.7.1.6 Comparative Summary

The preceding analysis examined each hypothesis group independently. H1 tested the direct effects of organizational influencing factors on project outcomes, H2 examined the factors associated with AI-PM utilization, H3 evaluated the effect of AI-PM on project outcomes, and H4 tested the mediating role of AI-PM in the relationship between influencing factors and project outcomes.

Table (74) integrates these findings into a comparative summary and shows how the individual pathways are connected within the proposed theoretical model. The comparison highlights the relative explanatory power of the models, the strongest predictors and outcomes, and the way in which the mediation findings clarify the relationships identified in H1, H2, and H3.

Table (74): Comprehensive Comparative Summary

Metric	H1: IVs → Outcomes	H2: IVs → AI-PM	H3: AI-PM → Outcomes	H4: Mediation Model	Interpretation
Main Effect R ² / Path Coefficient	23.50%	25.20%	60.00%	88% mediated	AI-PM implementation explains 2.4x more variance than direct factor effects; mediation model shows 88% approximately of IV effects work through AI-PM
Strongest Sub-Effect	Workforce: 24.4%	Infrastructure: 27.1%	Decision-Making: 51.3%	Full mediation pathway	Decision-making is strongest outcome (51.3%); full mediation means ALL IV effects require AI-PM as intermediary
# Significant Sub-Factors	1 of 6 (17%)	2 of 6 (33% in final model)	7 of 7 (100%)	2 of 3 paths significant	Only workforce development retains significance in H1's final model; infrastructure compatibility and workforce development remain significant for H2. All outcomes benefit from AI-PM (100%); only 2 of 3 paths significant in mediation (IVs→AI-PM and AI-PM→Outcomes; direct effect non-sig)

Strongest Individual Predictor	Workforce (r=.494)	Infrastructure (r=.521)	Decision-Making (r=.716)	Path B: AI-PM→Outcomes (1.036*)**	Decision-making shows 40% higher correlation than infrastructure; mediation model confirms AI-PM→Outcomes is strongest path (1.036 path coefficient)
Weakest Individual Predictor	Cost (r=.273; not sig in regression)	Privacy (r=.191; marginally sig)	Time Efficiency (r=.492)	Path C' (Direct): 0.125 (NS)	Direct IV effects on outcomes weakest (0.125, p=.455); all outcomes improve with AI-PM even if cost/privacy weak as direct factors
Effect Size Ranking	Workforce > Infrastructure > Ethics > Resistance > Privacy > Cost	Infrastructure > Workforce >> Resistance/Cost/Privacy/Ethics	Decision-Making > Risk ID > Quality > Communication > Data Accuracy > Data Analysis > Time Efficiency	Path A (0.889***) = Path B (1.036***) >> Path C' (0.125 NS)	Both adoption drivers and AI-PM effects are strong; direct effects negligible
Model Support Rate	1/6 (17%)	6/6 simple; 2/6 final multiple	7/7 (100%)	Full mediation: 100%	Workforce development is the most robust predictor identified across both H1 and H2's final models; AI-PM shows perfect support (100%) as the mediating mechanism, which remains the study's central finding
Variance Explained	23.5% (combined 6 IVs)	25.2% (combined 6 IVs)	60% (single mediator)	1.046 total effect; 88% indirect	Single AI-PM mediator explains 2.4x more variance than all 6 organizational factors combined
Organizational Factors Role	Direct influence on outcomes	Enable AI-PM adoption	Not tested in simple regression	INDIRECT ONLY: 88% mediated	H1 shows factors directly matter; H2 shows they drive adoption; H4 reveals ALL their outcome effects work through AI-PM
AI-PM Role	Not tested	Mediating variable (adopted if factors strong)	Direct strong predictor	CRITICAL MEDIATOR: 100% of significant IV effects flow through	AI-PM is the lynchpin: adoption depends on factors; outcomes depend on AI-PM; factor effects on outcomes require both
Model Fit Quality	— (Regression models)	— (Regression models)	— (Correlation/Regression)	CFI=.917 (Excellent), RMSEA=.087 (Good)	SEM mediation model achieves excellent fit (CFI>0.90); demonstrates robust theoretical framework
Direct vs Indirect Effects	All direct (no mediator)	All direct (no mediator)	All direct (no mediator)	Direct: 0.125 (NS); Indirect: 0.921; Total: 1.046*	Mediation model reveals: factors don't directly improve outcomes; their influence is approximately 88% indirect through AI-PM
Statistical Significance	All p<.05; most p<.001	Mixed: some p<.05, some p>.05 in combined model	All p<.001 (perfect significance)	Path A & B: p<.001; Path C': p=.455 (NS)	AI-PM effects universally significant (p<.001); mediation fully confirmed by non-significant direct effect

Strategic Implication	Organizational readiness matters for outcomes	Infrastructure + Workforce critical for adoption	AI-PM is THE leverage point for outcomes	Cannot improve outcomes by addressing factors alone—must implement AI-PM	Organizations need factors (H1/H2) AND implementation (H3) AND mediation (H4) for success
Priority for Organizations	Improve: Infrastructure, Workforce, Manage Resistance	Upgrade Infrastructure; Develop Workforce	Implement & utilize AI-PM practices broadly	Make AI-PM adoption PREREQUISITE for outcome improvement	H1+H2: Enable adoption (necessary). H4: AI-PM use is sufficient; without it, enablers don't deliver outcomes
ROI Pathway	Factors → Outcomes (direct)	Factors → AI-PM adoption	AI-PM → Outcomes	Factors → AI-PM → Outcomes (full chain required)	Complete ROI chain: Invest in factors; drive adoption; get outcomes. Breaking chain at any point reduces ROI to zero
Theoretical Framework Validation	✓ Direct effects supported	✓ Adoption drivers identified	✓ AI-PM mediator validated	✓✓ Full mediation confirmed (critical finding)	Three-level model (Factors→Adoption→Outcomes) fully validated; mediation hypothesis strongly supported

The comparative results indicate that AI-PM explains substantially more variance in project outcomes than the direct organizational-factor model. H1 explains 23.5% of the variance in outcomes, H2 explains 25.2% of the variance in AI-PM utilization, and H3 explains 60.0% of the variance in overall project outcomes. H4 further indicates that the relationship between organizational influencing factors and project outcomes operates primarily through AI-PM utilization.

The findings therefore position AI-PM as the central transformation mechanism linking organizational readiness to project success. Organizational factors remain important because they support AI-PM adoption, while AI-PM utilization is the pathway most directly associated with improvements in project outcomes.

Hypothesis Key Findings

The consolidated hypothesis-testing results are presented in Table (75). The table summarizes the principal statistical evidence for H1, H2, H3, and H4, including the relationships tested, explained variance, regression coefficients, significance levels, and hypothesis decisions.

Table (75) Hypothesis Key Findings

Hypothesis	Variable/Path	R	R ²	B (Effect)	F	t	p-value (Simple)	p-value (Multiple)	Result	Correlation (r)
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H1 MAIN	All IVs → Outcomes	0.485	0.235	0.61	30.989	5.567	0	0	STRONGLY SUPPORTED	0.485
H1A	Privacy → Outcomes	0.275	0.076	1.52	8.291	2.88	0.005	0.858	SUPPORTED	0.275
H1B	Resistance → Outcomes	0.345	0.119	1.82	13.601	3.688	0	0.49	STRONGLY SUPPORTED	0.345
H1C	Cost → Outcomes	0.273	0.074	1.28	8.123	2.85	0.005	0.787	SUPPORTED	0.273
H1D	Infrastructure → Outcomes	0.463	0.214	2.75	27.518	5.246	0	0.123	VERY STRONG	0.463
H1E	Workforce → Outcomes	0.494	0.244	2.91	32.573	5.707	0	0.009	STRONGEST	0.494
H1F	Ethics → Outcomes	0.314	0.099	1.97	11.075	3.328	0.001	0.619	SUPPORTED	0.314
H2 MAIN	All IVs → AI-PM	0.502	0.252	0.54	33.976	5.829	0	0	STRONGLY SUPPORTED	0.502
H2A	Privacy → AI-PM	0.191	0.037	0.9	3.832	1.957	0.053	0.21	MARGINAL	0.191
H2B	Resistance → AI-PM	0.341	0.116	1.53	13.25	3.64	0	0.66	SUPPORTED (simple)	0.341
H2C	Cost → AI-PM	0.325	0.105	1.29	11.89	3.448	0.001	0.693	SUPPORTED (simple)	0.325
H2D	Infrastructure → AI-PM	0.521	0.271	2.63	37.599	6.132	0	0.013	VERY STRONG	0.521
H2E	Workforce → AI-PM	0.527	0.278	2.64	38.83	6.231	0	0.007	STRONGEST	0.527
H2F	Ethics → AI-PM	0.335	0.112	1.79	12.74	3.57	0.001	0.549	SUPPORTED (simple)	0.335
H3 MAIN	AI-PM → Outcomes	0.775	0.6	0.91	151.59	12.312	0	0	PERFECT	0.775
H3A	AI-PM → Decision	0.716	0.513	0.17	106.2	10.31	0	0	VERY STRONG	0.716
H3B	AI-PM → Quality	0.675	0.456	0.15	84.53	9.194	0	0	VERY STRONG	0.675
H3C	AI-PM → Data Acc.	0.566	0.321	0.12	47.2	6.87	0	0	STRONG	0.566
H3D	AI-PM → Data Anal.	0.495	0.245	0.1	32.1	5.67	0	0	STRONG	0.495
H3E	AI-PM → Risk ID	0.677	0.459	0.15	85.4	9.24	0	0	VERY STRONG	0.677

H3F	AI-PM → Time Save	0.492	0.242	0.09	31.8	5.64	0	0	STRONG	0.492
H3G	AI-PM → Comm.	0.629	0.396	0.14	62.3	7.89	0	0	STRONG	0.629
H4 MEDIATION	IVs → AI-PM → Outcomes	-	85%	Indirect=1.036	-	-	Indirect 0.001	Direct 0.455 (NS)	FULL MEDIATION	-

Table (75) confirms the overall pattern of the hypothesis results. H1 demonstrates a significant relationship between the organizational influencing factors and project outcomes, explaining 23.5% of the variance. H2 shows that the influencing factors explain 25.2% of the variance in AI-PM utilization, with infrastructure and workforce development emerging as the strongest predictors in the final model.

H3 demonstrates a strong relationship between AI-PM utilization and project outcomes, explaining 60.0% of the variance in overall outcomes. Among the specific outcomes, decision-making and risk identification showed the strongest relationships with AI-PM. H4 further confirms that AI-PM functions as the principal mediating mechanism linking organizational influencing factors to project outcomes.

Taken together, the findings support the proposed three-level framework in which organizational factors contribute to AI-PM adoption, AI-PM utilization improves project outcomes, and the effects of organizational factors on outcomes operate primarily through AI-PM.

Detailed sub-hypothesis statistics, effect-size rankings, model-specific significance results, and the supporting calculations for the comparative findings are provided in Appendix C under “Comparative Hypothesis Results.”

4.7.1.7 OVERALL HYPOTHESIS SUPPORT RATE

This final synthesis evaluates the cumulative empirical support for H1, H2, H3, and H4. Across the four hypothesis groups, 20 hypotheses were tested: six for H1, six for H2, seven for H3, and one for H4. Based on the final hypothesis decisions, 16 hypotheses were supported, representing an overall support rate of 80%.

The results provide substantial support for the proposed three-level framework:

Organizational Factors → AI-PM Utilization → Project Outcomes

The support rates differ across the hypothesis groups. H1 received support for 5 of 6 hypotheses, H2 retained 3 of 6 significant predictors in the final combined model, H3 received support for all 7 outcome relationships, and H4 supported the mediation pathway.

Table (76) Support Rate Across All Hypotheses

Support Rate Across All Hypotheses					
Hypothesis Group	Total Hypotheses	Supported	Not Supported	Support Rate	Key Finding
H1: Direct IV → Outcomes	6	1	5 (Privacy, Resistance, Cost, Infrastructure, and Ethics lose significance once all six factors are considered jointly)	0.17	Workforce development is the only factor that retains an independent direct effect on project outcomes in the final model; infrastructure compatibility, though significant at an earlier step, is substantially explained by its overlap with workforce development
H2: IV → AI-PM Adoption	6	2 (final model)	4	33% final (100% main)	Main effect supported; only Infrastructure & Workforce remain significant in combined model
H3: AI-PM → Outcomes	7	7	0	1	Perfect support across all 7 outcomes identified in this study; no exceptions
H4: Mediation	1	1	0	1	Full mediation confirmed; approximately 88% of IV effects mediated through AI-PM
TOTAL	20	11	9	0.55	Workforce development and, to a lesser extent, infrastructure compatibility emerge as the most consistently influential factors identified in this study; AI-based project management remains the strongest and most consistent mechanism linking organizational conditions to project outcomes

The results show that H3 provides the most consistent support, with all seven outcome relationships statistically significant. H4 also supports the proposed mediation pathway, while H1 and H2 show some loss of individual significance when predictors are evaluated simultaneously.

Overall, the findings indicate that organizational factors are important enablers of AI-PM adoption, but AI-PM utilization is the pathway most strongly associated with project outcomes. Detailed group-specific support-rate interpretations and strategic implications are provided in Appendix C under “Overall Hypothesis Support Rate: Detailed Interpretation.”

4.8 Interpretation and Implications of the Mediation Effect

The structural equation modeling results show that AI-Based Project Management mediates approximately 88% of the total effect of the independent variables on project outcomes.

4.8.1 What this means in practical terms:

The majority of the positive effects come from enabling factors only after they lead to full adoption and effective utilization of AI tools. Specifically, the following enabler readiness variables contribute positively through AI adoption:

- Infrastructure compatibility
- Workforce development
- Resistance to change management
- Data privacy and security
- Ethical considerations
- Cost mitigation

These factors improve project outcomes mainly when they support the active and sustained use of AI-based project management systems.

Variables that showed weak or non-significant direct influence on project outcomes (such as cost and ethical considerations) still play important roles as enablers of AI utilization but do not directly influence outcomes unless mediated by AI utilization.

4.8.2 Theoretical implications:

This strong mediation effect confirms the conceptual model, which posits that enablement through organizational readiness influences project outcomes predominantly via the pathway of AI implementation. It highlights that studies focusing only on direct relationships may overlook the critical role of AI utilization as the main driver of performance improvement.

4.8.3 Practical implications for organizations:

- Improving enabler readiness alone, such as providing workforce training or updating infrastructure, will not significantly improve project outcomes unless these improvements translate into real AI utilization.
- It is crucial that organizations move beyond just preparing for AI and focus on comprehensive AI utilization and integration into project management workflows.

- Change management programs, technical upgrades, and budget allocation must aim toward enabling effective AI usage, not only readiness on paper.

4.8.4 Support from qualitative evidence:

Our interviews provide concrete examples supporting this mediation. For example, one project manager described how investments in staff training only improved project performance after new AI tools were actually launched and used across multiple projects. Another manager remarked, "We spent two years updating our infrastructure, but project scores only improved once the AI platform was rolled out and adopted on a daily basis." Such accounts confirm the pathway identified statistically and highlight the real-world relevance of the mediation effect.

4.9 Qualitative Thematic Analysis

The qualitative analysis explored the factors influencing AI utilization in project management within Saudi organizations, with particular attention to the independent variables, the AI-based project-management mediating variables, and the project-management outcome variables.

The findings integrate technical, organizational, financial, and ethical dimensions of AI utilization. The interview evidence indicates that successful AI adoption requires an integrated management approach combining workforce development, technical compatibility, ethical governance, data protection, change management, and financial planning, while also considering the local organizational context.

Interviews continued until thematic saturation was reached. Ten expert practitioners were interviewed; no substantially new themes emerged after the seventh interview, while the final three interviews confirmed the themes already identified. The qualitative findings provide contextual depth for interpreting the quantitative results and contribute to the triangulation of the overall study findings.

4.9.1 Independent Variables (Factors Influencing AI utilization) - 6 Themes

Six themes emerged from the interviews as organizational factors influencing AI utilization:

- data privacy and security;
- resistance to change;
- cost of AI implementation;
- compatibility with existing infrastructure;
- workforce development; and
- ethical considerations.

The findings indicate that data privacy and security, ethical governance, and resistance to change are prominent considerations in AI adoption. Participants described the importance of governance

frameworks, access controls, encryption, regulatory compliance, and responsible data handling in building trust in AI systems.

Resistance to change was associated with unfamiliarity with AI tools, concerns about job displacement, and limited digital or analytical literacy. Participants indicated that training, leadership engagement, and practical workshops helped reduce resistance and encouraged acceptance.

Cost and infrastructure compatibility were identified as important strategic and technical considerations. Participants described the need to evaluate expected benefits, manage implementation costs, upgrade legacy systems, and address data and software-integration challenges. Workforce development and ethical governance were also identified as necessary for sustainable and responsible AI utilization.

Table (77) presents the detailed thematic summary of the six independent-variable themes, including interview frequencies, representative quotations, and interpretive summaries. The full table and supporting interview evidence are provided in Appendix C under **“Qualitative Thematic Analysis: Independent Variables.”**

4.9.2 Mediating Variable: AI-Based Project Management — 5 Themes

Five themes emerged regarding the practical use of AI-based project management:

- process streamlining;
- resource allocation;
- task prioritization;
- progress reporting; and
- communication.

The interviews indicate that AI-based project management supports operational efficiency through process automation, data-driven resource allocation, task prioritization, progress monitoring, reporting, and team communication. These findings illustrate how AI-PM can function as a mediating mechanism by translating organizational readiness into practical project-management improvements.

Participants described the use of AI for automating routine reports, improving workflow visibility, identifying resource conflicts, prioritizing tasks, generating early alerts, and supporting communication among project stakeholders.

Table (78) presents the detailed thematic summary of the AI-PM mediating variables. The full table, interview quotations, and interpretive summaries are provided in Appendix C under **“Qualitative Thematic Analysis: Mediating Variables.”**

4.9.3 Dependent Variables: Project-Management Outcomes — 7 Themes

All seven project-management outcome themes identified through the study's conceptual framework were confirmed in the interviews:

- project quality;
- decision-making;
- data collection accuracy;
- data analysis and insight generation;
- risk identification accuracy;
- time efficiency; and
- communication and collaboration.

The findings indicate that AI-PM contributes to improvements across all seven outcome dimensions. Participants described benefits including earlier error detection, more accurate data capture, improved forecasting, faster decision-making, proactive risk identification, reduced administrative workload, and more effective stakeholder communication.

These findings are consistent with the quantitative H3 results, which showed statistically significant positive relationships between AI-PM utilization and all seven measured project-management outcomes. The qualitative evidence therefore provides contextual support for the breadth of the AI-PM effect observed in the quantitative analysis.

Table (79) presents the detailed thematic summary of the seven project-management outcomes, including interview frequencies, representative quotations, and interpretive summaries. The complete table and supporting interview evidence are provided in Appendix C under “**Qualitative Thematic Analysis: Project-Management Outcomes.**”

4.9.4 Synthesis of Qualitative Findings

Taken together, the qualitative findings support the proposed pathway:

Organizational factors → AI-PM utilization → Project-management outcomes

The independent-variable themes describe the organizational and technical conditions required for AI adoption. The mediating-variable themes describe how AI-PM is implemented in practice, while the dependent-variable themes describe the project improvements associated with its use.

The qualitative results therefore complement the quantitative findings by showing how organizational readiness is translated into project outcomes through actual AI-PM utilization. The detailed frequency information, interview quotations, thematic coding evidence, and supporting figures are presented in Appendix C.

4.10 Integration of Quantitative and Qualitative Findings (Triangulation)

Mixed-methods triangulation provides a comprehensive understanding of AI-based project management utilization and outcomes by validating quantitative statistical relationships through qualitative practitioner experience. This section systematically examines convergences, discrepancies, and the validated mediation mechanism across both methodological approaches.

4.10.1 Convergence Between Methods

Strong Convergence (High Agreement Between Methods) across quantitative and qualitative findings validates key relationships and enhances confidence in the proposed theoretical framework.

1. Workforce Development Impact

- Quantitative: Strongest correlation with AI-Based Project management ($r = 0.527$) and project outcomes ($r = 0.494$)
- Qualitative: Training gaps mentioned in 100% of interviews; "lack of adequate training" cited as key limiting factor
- Integration: Both methods strongly support workforce development as critical enabler

Qualitative Support: Thematic analysis confirmed this pattern. The "Workforce Development" theme appeared in all 10 interviews, with recurring phrases such as "training gaps," "skill development," and "digital literacy." One respondent noting: "Lack of adequate training limits the effective utilization of AI-based project management tools"

2. Time Savings Outcome

- Quantitative: Highest dependent variable mean score (8.50 ± 1.24 ; 84.95%)
- Qualitative: All 10 interviews mentioned time savings; ranked #1 tangible benefit
- Integration: Consistent recognition of AI's operational efficiency impact

3. Data Quality & Analysis

- Quantitative: High dependent variable means for data collection (8.35) and analysis (8.42)
- Qualitative: Nine themes mentioned data accuracy and insights
- Integration: Both confirm AI's significant contribution to information quality

4.10.2 Discrepancies and Contextual Explanations

While convergence is strong overall, some apparent discrepancies reflect nuanced relationships requiring contextual explanation.

1. Ethical Considerations Discrepancy:

- Quantitative: Highest independent variable mean (7.97, 79.71%) but not significant predictor ($p = 0.619$)
- Qualitative: Ethics mentioned in 80% of interviews but often as secondary concern.
- Explanation: Ethics was acknowledged as important but abstract; organizations lack concrete guidelines (as stated in interviews: *"Lack of clear regulations makes firms cautious"*), reducing its measurable impact on outcomes.

2. Cost as Non-Significant Predictor:

- Quantitative: Cost of AI implementation showed a significant simple correlation with AI-based project management utilization ($r = 0.325$) but did not retain a significant direct effect on project outcomes once all six influencing factors were considered jointly (final model $p = .787$).
- Qualitative: Cost was raised in all ten interviews, frequently cited as a barrier to adoption.
- Explanation: Cost appears to influence whether AI is adopted in the first place (hence its correlation with AI-based project management utilization), but organizations that adopt AI despite cost constraints achieve outcomes comparable to those of better-funded organizations. This suggests cost functions as a barrier to entry rather than a determinant of performance once AI is in use — a distinction consistent with Bughin et al.'s (2018) observation that financial constraints tend to shape whether organizations adopt AI at all, rather than how effectively they perform once adoption has occurred.

3. Infrastructure Compatibility: A Genuine Point of Divergence

- Quantitative: Infrastructure compatibility showed a strong correlation with AI-based project management utilization ($r = 0.521$) and was a significant predictor when first entered into the regression model ($p = .001$). However, once workforce development and ethical considerations were added, infrastructure compatibility no longer retained a significant independent effect on project outcomes (final model $p = .123$).

- **Qualitative:** Every interviewee (10 of 10) cited infrastructure integration challenges as a barrier, frequently naming specific systems (Primavera, Revit, SAP) that proved difficult to reconcile with AI tools.
- **Integration:** This represents a genuine, informative divergence between the two methods rather than straightforward convergence.

The qualitative unanimity suggests infrastructure compatibility is a real and keenly felt operational concern for practitioners, but the quantitative final model suggests its influence operates primarily through enabling AI-PM utilization (as confirmed in H2) rather than as an independent driver of project outcomes once AI is already in use. This is consistent with Korke et al.'s (2023) observation that legacy-system incompatibility functions chiefly as an adoption bottleneck rather than a performance determinant in its own right, practitioners experience infrastructure friction acutely during implementation, but once AI tools are operational, outcomes are shaped more by how well staff use them (workforce development) than by the infrastructure itself.

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4.10.3 Mediating Role Validation

The mediation mechanism represents the central theoretical contribution and is strongly validated across both quantitative and qualitative methods.

Quantitative Evidence: AI-PM fully mediates the relationship between organizational factors and outcomes. The direct effect is non-significant ($\beta = 0.125$, $p = 0.455$), while the indirect effect is highly significant ($p < 0.001$). Approximately 88% of organizational factors' effects on outcomes operate through AI-PM adoption. The modified SEM model achieves excellent fit (CFI = 0.917, RMSEA = 0.087), and AI-PM explains 2.4x more variance in outcomes (60%) than direct organizational factors (23.5%).

Qualitative Evidence: Practitioners universally recognize AI-PM as the essential mechanism through which organizational readiness produces outcomes. Concrete examples validate the mediation pathway: infrastructure investment enables AI deployment (producing 80% error reduction); workforce development improves utilization competency (enabling 8-10 hours/week time savings); change management reduces adoption resistance (permitting improved decision-making).

Explanation: Organizational readiness investments are necessary but insufficient. Their impact on outcomes is entirely conditional on effective AI-PM implementation. Organizations cannot achieve improvements through readiness alone; they must operationalize investments through deliberate AI-PM adoption. Many organizations fail because they invest in infrastructure and training without pursuing actual AI tool implementation and use.

4.11 Summary of Key Findings

4.11.1 Quantitative Findings:

The quantitative analysis tested 20 hypotheses across four groups, achieving an 80% overall support rate (16 of 20 hypotheses supported), providing robust validation of the three-level theoretical model.

Measurement Quality: All instruments demonstrated strong reliability ($\alpha \geq 0.879$) and validity (item-total correlations 0.43-0.97), confirming sound measurement properties.

H1 (Organizational Factors → Outcomes): 83% support. Six factors explain 23.5% of outcome variance ($R^2 = 0.235$, $p < 0.001$). Workforce Development ($R^2 = 24.4\%$) and Infrastructure Compatibility ($R^2 = 21.4\%$) are the strongest individual predictors.

H2 (Organizational Factors → AI-PM utilization): 50% final support. In the combined model, only Infrastructure Compatibility and Workforce Development remain significant independent predictors ($p < 0.05$), indicating these are the primary drivers of AI-PM utilization.

H3 (AI-PM → Outcomes): 100% perfect support. All seven outcome dimensions show highly significant relationships ($p < 0.001$). AI-PM utilization explains 60% of outcome variance ($R^2 = 0.60$)—a 2.4x amplification compared to direct organizational factor effects (23.5%).

H4 (Mediation): Full mediation confirmed. 88% approximately of organizational factors' effects on outcomes operate through AI-PM utilization. Direct effect non-significant ($\beta = 0.125$, $p = 0.455$); indirect effect significant ($p < 0.001$). Modified SEM achieves excellent fit (CFI = 0.917, RMSEA = 0.087).

Central Quantitative Finding: Organizational readiness is necessary but insufficient for project success. Its impact on outcomes is entirely mediated through AI-PM utilization. Without AI implementation, organizational factor improvements yield minimal outcome gains.

4.11.2 Qualitative Findings:

Qualitative analysis of 10 expert practitioner interviews identified 18 themes across three variable categories, validating and contextualizing quantitative findings.

Independent Variables (6 themes were identified, and each theme appeared in 8 to 10 of the 10 interviews.): All six organizational factors—Data Privacy & Security, Resistance to Change, Cost, Infrastructure Compatibility, Workforce Development, and Ethical Considerations—emerged as universally recognized influencing factors. Practitioners consistently emphasized infrastructure upgrades and training as critical for AI utilization success.

Mediating Variables (5 themes; 4 appeared in 9–10 of 10 interviews, while 1 appeared in 4 of 10 interviews): Four themes emerged with universal frequency (9-

10/10): Streamlining Process (automation reducing report time from days to hours), Resource Allocation (over-allocation reduced approximately 20%), Progress Reporting (automated alerts catching delays early), and Communication (common dashboards improving coordination). Task Prioritization appeared less frequently (4/10), indicating emerging adoption.

Dependent Variables (7 themes; 10/10 interviews - perfect universality): All seven outcome benefits emerged with perfect consensus across all 10 interviews:

- Improving Project Quality (early error detection, client satisfaction increased)
- Enhancing Decision-Making (faster, data-driven decisions)
- Data Collection Accuracy (80% reduction in data duplication errors)
- Data Analysis (predictive analytics uncovering hidden patterns)
- Risk Identification (early warnings preventing major issues)
- Time Saving (8-10 hours/week saved per manager)
- Communication (transparent stakeholder updates building trust)

Central Qualitative Finding: Complete practitioner consensus on AI-PM benefits across all seven outcome dimensions, validating the quantitative H3 perfect support (100%) through lived experience.

4.11.3 Integrated Findings:

Strong convergence between quantitative and qualitative results:

- Quantitative 80% support + universal qualitative themes = robust framework validation
- Quantitative 88% mediation + practitioner descriptions of AI as "mechanism" = confirmed mediation pathway
- Quantitative 2.4x amplification + practitioner reports of "substantial transformation" = coherent narrative

Discrepancies explained through context: Ethics and Cost show lower independent effects in H2 because they operate through Infrastructure/Workforce decisions. Task Prioritization's lower qualitative frequency (4/10) suggests emerging rather than mature implementation.

4.11.4 Conclusion

The comprehensive mixed-methods analysis across quantitative hypothesis testing and qualitative thematic analysis consistently demonstrates that organizational and technical factors significantly influence AI-based project management utilization, which in turn substantially enhances project outcomes in Saudi design and consultancy engineering firms.

Quantitative Foundation: The hypothesis testing results provide strong empirical validation of the three-level theoretical model. An overall 80% hypothesis support rate (16 of 20 hypotheses) establishes the robustness of the proposed framework. Specifically, organizational factors directly predict project outcomes (H1: 83% support), though with moderate effect sizes ($R^2=23.5\%$). These same factors drive AI-PM utilization (H2: 50% support in combined models), with Infrastructure Compatibility and Workforce Development emerging as the primary independent predictors. Most critically, AI-based project management shows perfect support across all seven outcome dimensions (H3: 100% support), explaining 60% of outcome variance—a 2.4x amplification compared to direct factor effects.

The mediation analysis (H4) represents the core finding: AI-PM fully mediates the relationship between organizational factors and project outcomes, with approximate 88% of the influence operating through the mediation pathway. The non-significant direct effect ($\beta=0.125$, $p=0.455$) definitively establishes that organizational readiness factors alone do not automatically produce outcome improvements; rather, these improvements materialize only when organizational readiness catalyzes effective AI-PM utilization and implementation.

Qualitative Validation: Interviews with 10 expert practitioners across Saudi design and consultancy engineering firms validate and contextualize these quantitative findings. All six independent variable themes emerged across interviews (frequency 8-10/10), confirming that organizational factors are universally recognized as critical for AI utilization. The five mediating variable themes (frequency 4-10/10) reveal the practical mechanisms through which AI-PM operates: process automation, resource optimization, task prioritization, progress reporting, and enhanced communication. Most significantly, all seven dependent variable themes emerged with perfect universal frequency (10/10 interviews), indicating complete practitioner consensus that AI-PM produces comprehensive benefits across all project management dimensions.

Practitioners consistently reported tangible improvements: data duplication errors reduced by 80%, project managers saving 8-10 hours weekly, decision accuracy improved through data-driven dashboards, early risk identification preventing major issues, and enhanced stakeholder trust through transparent communication. These qualitative insights translate the quantitative coefficients into lived organizational reality.

Integrated Conclusion: The convergence between quantitative and qualitative findings confirms that the three-level mediation model (Organizational Factors → AI-PM utilization → Project Outcomes) accurately represents how AI-based project management creates value in engineering project environments. The analysis reveals a coherent pattern: while organizational readiness is necessary (H1 support), it is insufficient without effective AI implementation (H4 mediation). Infrastructure and workforce development drive utilization (H2 primary drivers), and utilization in turn delivers universal improvements across all outcome dimensions (H3 perfect support).

The 2.4x amplification of variance explained when organizational factors work through AI-PM (60% vs. 23.5%) underscores AI-PM's role as a critical transformation mechanism. Organizations cannot achieve superior project outcomes by addressing readiness factors alone; they must operationalize these improvements through deliberate AI-PM utilization and effective utilization.

4.12 Chapter 4 Summary

Chapter 4 presented empirical results confirming instrument reliability (Cronbach's $\alpha = 0.815$ to 0.922 , main study), with 103 respondents drawn from mixed hierarchical levels — weighted toward project engineers, engineers, and project managers, with 58% reporting over 10 years of experience — primarily from medium to large Saudi design and consultancy firms (92% medium or large). Descriptive statistics showed positive perceptions (means 3.8 to 4.1), strong correlations ($r = 0.3$ to 0.85), and no multicollinearity concerns ($VIF < 5$); SEM achieved acceptable fit ($CFI = 0.917$, $RMSEA = 0.087$), with AI-based project management fully mediating the pathway from influencing factors to outcomes. Hypothesis testing supported 55% of the individual relationships examined (H1: 1/6, H2: 2/6, H3: 7/7, H4: confirmed), with workforce development emerging as the single most consistent and robust predictor across both direct outcomes and AI-PM utilization, and infrastructure compatibility remaining significant specifically for enabling AI-PM adoption. Qualitative themes showed strong agreement across the ten interviews on project-management outcomes, reinforcing the quantitative SEM results through practitioner insights on time savings and improved decision-making. Detailed outputs (Tables 30–74) reside in Appendix C; these findings support the mediation model as the study's central contribution within the Saudi context.

CHAPTER 5

5 Conclusion and Recommendations

5.1 Summary of Key Findings

This study tested the conceptual model examining organizational, technical, and ethical factors' influence on AI-based project management utilization and project outcomes in Saudi design/consultancy engineering projects. All five objectives were achieved.

Quantitative Findings:

The SEM model confirmed AI-based project management as a robust mediator ($r = 0.775$), explaining 60% of the variance in project outcomes, with 88% of the effect of organizational and technical factors operating indirectly through AI-based project management. Hypothesis H3 received full support across all seven outcome dimensions, confirming AI-PM utilization itself as the strongest and most consistent driver of project outcomes. Among the six organizational and technical factors examined, workforce development emerged as the most robust predictor across both direct outcomes and AI-PM adoption, while infrastructure compatibility, resistance to change, data privacy and security, and cost primarily influenced outcomes indirectly, through their effect on AI-PM utilization rather than as independent direct drivers.

Qualitative Findings:

Thematic analysis of 10 interviews (thematic saturation reached at interview 7) validated the quantitative findings consistently highlighting training gaps, infrastructure limitations, and time savings as AI's principal benefits.

Integrated Conclusion:

These convergent findings from the triangulation design robustly validate the model's applicability to Saudi engineering firms.

5.2 Action Plan Recommendations

5.2.1 Summary of the Strategic Recommendation

The following table presents summary of prioritized and measurable recommendations that are directly derived from the eight main empirical results of the study. The recommendations clarify the required actions, outline practical implementation mechanisms, and specify realistic timeframes suitable for design and consultancy engineering firms in Saudi Arabia.

Recommendation Prioritization Note:

Recommendations are scaled to firm size/capacity, with primary focus on workforce development, the factor that retained significance across both the direct-outcomes and AI-PM-adoption models, and infrastructure compatibility, which retained significance specifically for enabling AI-PM adoption. Other factors — resistance to change, data privacy and security, ethics, and cost — showed significant individual associations and were consistently emphasized in the qualitative interviews, but did not retain independent significance once all six factors were considered jointly; these are treated as important governance and risk-management considerations rather than primary statistical drivers. Smaller firms (9% of the sample) can implement via pilots/shared services before full scaling, ensuring feasibility across organizational contexts.

Table (80) Strategic Recommendation and Implementation Timeline

Result	Recommendation	Implementation Method	Timeframe
Result 1: AI-based project management significantly improves all 7 project outcomes (H3: 100% supported, $R^2=60\%$, $r=0.775$).	1.1: Institutionalize AI-PM as a mandatory standard for all design/consultancy projects. Note; Smaller firms may implement AI-PM standards first on selected priority projects and expand gradually based on demonstrated benefits and available budget.	- PMO develops policy requiring a minimum AI tools per project phase; - trains project managers; - audits quarterly compliance; - links to KPI bonuses	Total: 12 months (3m policy development, 6m training, and 3m compliance check)
	1.2: Set a quantified reduction target for routine task time through AI utilization, calibrated from baseline and pilot results.	- Select top 3 AI tools (scheduling, risk, reporting); - pilot 20% projects; scale to 80%; - measure monthly via PMIS time-tracking	24 months phased rollout
	1.3: Establish AI-PM Center of Excellence reporting to C-level.	- Form a team of COE; - Develop standardized templates; - Certify practitioners annually.	18 months establishment + ongoing certification
Result 2: 88% mediation - Organizational factors improve outcomes primarily through AI-PM adoption (H4 confirmed)	2.1: Prioritize AI-PM utilization investments over general organizational readiness.	Reallocate a specific PMO budget from generic training to AI tool procurement/training;	12 months budget shift + 24 months ROI measurement

Result	Recommendation	Implementation Method	Timeframe
		track ROI via pre/post outcome metrics	
	2.2: Design an integrated "Factors→AI→Outcomes" maturity model for annual assessment.	- Create 5-level maturity scale (IVs→AI-PM→DVs); - assess all projects annually; - target 40% improvement in Level 3+ firms	9 months model design + annual assessment
Result 3: Workforce development is strongest predictor of both AI-PM adoption and outcomes (H1E/H2E, B=2.91)	3.1: Prioritize/require AI-PM certification for project managers, starting with senior roles.	- Partner SDAIA/PMI for certified "AI-PM Practitioner" program; - required for promotions; achieve 88% certification coverage.	24 months (100% senior PMs Year 1, all PMs Year 2)
	3.2: Launch "AI Upskilling Academy" with 500 annual training slots.	- Quarterly 40-hour bootcamps (AI tools, ethics, integration); - track 30% productivity gain via pre/post assessments.	6 months launch + 500 slots/year
Result 4: Infrastructure compatibility is the strongest predictor of AI-based project management adoption after workforce development (H2D supported), though it does not retain an independent direct effect on project outcomes once workforce development is accounted for (H1D not significant in the final combined model)	4.1: Conduct enterprise-wide AI infrastructure audit and remediation plan.	- Hire a certified vendor for 100% system compatibility assessment; - prioritize top 20% mission-critical systems.	9 months (3m audit, 6m remediation)
	4.2: Standardize API integration layer for all PMIS and AI tools.	- Develop a common API gateway; - certify a minimum number of vendor integrations; required for all new AI tool purchases.	15 months (12m development, 3m certification)
Result 5: Ethical considerations show high descriptive	5.1: Develop AI Ethics Charter as governance	Create 12-point (bias mitigation,	6 months charter + annual refresh

Result	Recommendation	Implementation Method	Timeframe
importance (H1F: 79.71% mean score, frequent qualitative mention) but secondary effect in combined models (p=0.619).	framework , endorsed by C-level executives.	transparency, accountability); • mandatory annual ethics training (4 hours); • 100% executive sign-off.	
	5.2: Establish AI Ethics Review Board for all tool deployments	• 7-member board (legal, ethics, PM, IT, SDAIA); • pre-approve all AI deployments; quarterly compliance reports.	4 months establishment + ongoing
Result 6: Resistance to change shows a significant individual association with both outcomes and AI-PM adoption (77.28% mean agreement in the survey; confirmed in all 10 interviews), though it does not retain independent significance once all six factors are considered jointly (H1B and H2B not significant in the final combined models)	6.1: Launch "AI Change Champions" program with 20% employee coverage	• Identify champions (10% workforce); • 3-day training; monthly peer sessions; • track 25% resistance reduction via surveys.	12 months (6m champions, 6m scale)
	6.2: Implement "AI Success Story Dashboard" for weekly visibility	• Collect weekly wins (time saved, risks caught); • PMO dashboard; all-hands meetings; • target 40% attitude improvement.	3 months launch + weekly updates
Result 7: Data privacy and security concerns show a moderate individual association with both outcomes and AI-PM adoption (74.66% mean agreement in the survey), though this factor does not retain independent significance once all six factors are considered jointly (H1A and H2A not significant in the final combined models)	7.1: Deploy "AI Data Shield" protocol for all project data	• Mandatory encryption and anonymization for all AI inputs; • SDAIA or equivalent compliance audit; 100% tool certification.	9 months (6m protocol, 3m audit)
	7.2: Conduct annual "Privacy Impact Assessments" for all AI tools	• Standardized template; legal and IT review; • publish executive summaries; • maintain 95% compliance rate.	3 months template + annual cycle

Result	Recommendation	Implementation Method	Timeframe
Cost shows a barrier-to-entry role (H1C: p=0.787; H2C: p=0.693, both non-significant in final models)	8.1: Develop AI Cost-Benefit Calculator as decision-support tool for major AI investments.	- PMO develops standardized ROI model; - strongly recommended for purchases >50K SAR, mandatory for PMO-managed investments. - target 3:1 ROI minimum.	4 months tool development + mandatory use
	8.2: Establish "AI Vendor Pre-Qualification Framework" with cost ceilings.	- Annual vendor scoring (cost 40%, efficacy 40%, compliance 20%); - pre-approved list only; 20% cost reduction target.	6 months framework + annual refresh

5.2.2 Details of Strategic Recommendation

The detailed recommendations presented below elaborate each action from Table (80), providing comprehensive guidance for implementation. For each empirical result, the recommendations specify:

- The precise organizational action required,
- Step-by-step implementation procedures involving key stakeholders and resources, and
- Realistic timeframes calibrated for design and consultancy engineering firms operating within Saudi Arabia's regulatory and market context.

These recommendations directly translate the study's statistical findings into executable strategies aligned with Vision 2030 digital transformation objectives.

5.2.2.1 Result 1

AI-based project management significantly improves all seven project outcomes (decision-making, project quality, data collection accuracy, data analysis, risk identification accuracy, time-saving for project managers, and effective communication), with H3 fully supported and AI-PM explaining approximately 60% of the variance in project outcomes.

5.2.2.1.1 Recommendation 1.1

Institutionalize AI-based project management as an organizational standard for design and consultancy projects, with phased utilization tailored to firm size and capacity.

Elaborated recommendation

Organizations managing design and consultancy engineering projects should formally utilize AI-based project management as a standard practice across all project phases, rather than leaving its use to individual preferences or isolated pilots. This means that AI-PM should be embedded in the organization's project management methodology, procedures, and governance documents, ensuring that AI tools are systematically used to support decision-making, planning, monitoring, and reporting.

This recommendation is grounded in the quantitative finding that AI-based project management explains 60% of the variance in project outcomes and is the single strongest predictor in the model. At the same time, the pathway to institutionalization should reflect organizational size and resource levels: medium and large firms can move toward broad, policy-based utilization, whereas smaller firms may begin with a limited set of high-impact projects and scale up as capacity and budgets allow.

Implementation method

- The Project Management Office (PMO), in collaboration with senior management and IT, prepares and approves an AI-PM policy and procedure manual that specifies where and how AI tools must be used (for example, in scheduling, risk identification, progress reporting, and communication), with lighter, pilot-focused requirements for smaller firms or units with limited resources.
- The policy may require the use of a minimum set of AI-enabled functionalities and gradually increase the AI-supported processes per project phase to ensure meaningful utilization.
- The PMO designs a comprehensive training program to ensure that all project managers and selected team members are able to use the required tools effectively.
- Compliance with AI-PM standards is monitored through monthly or quarterly PMO audits of active projects, checking actual use of AI tools and the quality of outputs.
- The organization links adherence to AI-PM practices, and improvements in the seven outcome areas, with performance evaluation and KPIs at project and PMO levels, creating incentives for consistent application.

Timeframe

- Approximately 12 months in three stages:
 - 3 months for policy and procedure development, stakeholder consultation, and formal approval.
 - 6 months for training design and delivery to all project managers and key staff.
 - 3 months for initial implementation and the first compliance audit cycle, with adjustments based on feedback.

5.2.2.1.2 Recommendation 1.2

Set a quantified target to reduce time spent on routine project management tasks through AI-PM utilization, based on measured baseline and pilot results (e.g., in the 30–50% range where achievable)

Elaborated recommendation

To translate the demonstrated effect of AI-PM on time-saving into a concrete objective, organizations should explicitly aim to reduce the time spent by project managers and teams on repetitive, low-value tasks such as manual data entry, report preparation, and basic status consolidation by around 50%. This target will help focus utilization on measurable efficiency gains and free project managers to focus on strategic and analytical tasks.

The statistical results of this study confirm that AI-based project management has a significant positive effect on time efficiency as one of the seven outcomes, but they do not prescribe a specific percentage reduction. Therefore, the numeric target should be derived from each organization's own baseline measurements and pilot projects, using the study's findings as justification for aiming at substantial, rather than marginal, improvements.

Implementation method

- The PMO, together with IT and selected project managers, identifies the most time-consuming routine activities in current project management practice for example, schedule updating, risk log updates, status and progress report generation.
- Based on this analysis, the organization selects three priority AI tools such as AI-assisted scheduling, AI-driven risk analytics, and automated reporting dashboards, that can directly automate or substantially accelerate these activities.
- An initial pilot phase is conducted on a realistic subset of projects, for example, 20% of active projects, to test the tools, measure time savings, and refine processes.
- After evaluating pilot results, the organization scales up AI automation to cover a larger number of projects, for example, 50% and then 80% as PMO suggestion based on the project situation and organization readiness, accompanied by targeted training and support.
- Time savings are measured monthly using project management information systems PMIS logs, time-tracking reports, or standardized self-reporting templates, comparing baseline (pre-AI) and (post-AI) figures for key routine tasks.
- Based on the measured results, the organization may reevaluate the 50% target (upward or downward) to stay realistic and aligned with our actual capabilities

Timeframe

- Around 24 months in a phased approach:
 - 3–6 months for baseline analysis, selection of tools, and setup.
 - 6–9 months for the initial pilot on about 20% of projects.

- 9–12 additional months to scale AI automation gradually to a target of 70–80% of projects, with ongoing monitoring and adjustment.

5.2.2.1.3 Recommendation 1.3

Establish an AI-based Project Management Center of Excellence (AI-PM COE) reporting to executive leadership.

Elaborated recommendation

To sustain and continuously improve AI-based project management, organizations should create a dedicated Center of Excellence that coordinates AI-PM initiatives, develops standardized practices, supports implementation, and monitors impact. Positioning this COE under executive sponsorship (for example, reporting to the CEO or a high-level steering committee) ensures that AI-PM remains a strategic priority and not only a technical or experimental initiative. While the Project Management Office (PMO) focuses primarily on the governance and execution of projects, the proposed AI-PM Center of Excellence (COE) functions as a specialized capability unit that develops AI-related standards, methods, and competencies to be applied by the PMO and project teams

Implementation method

- Senior management approves the creation of an AI-PM Center of Excellence with a clear mandate, responsibilities, and reporting lines.
- The COE is staffed with a multidisciplinary team, for example: experienced project managers, IT specialists, data/AI specialists, and a representative responsible for ethics, governance, and alignment with national AI strategies and regulations.
- The COE develops a portfolio of standardized AI-PM templates and tools (for example, risk analysis models, reporting formats, dashboards, decision-support checklists) that can be used across design and consultancy projects to ensure consistency and quality.
- The COE designs and delivers specialized training and certification programs in AI-based project management for internal staff, with clear levels: introductory, intermediate, and advanced.
- The COE establishes a monitoring and evaluation framework to track key indicators associated with AI-PM, utilization rates, outcome improvements, user satisfaction, and regularly reports these indicators to executive leadership.
- The COE encourages internal knowledge sharing, for example through communities of practice, lessons-learned sessions, and internal publications documenting successful AI-PM applications and challenges.

Timeframe

- Approximately 18 months for establishment and stabilization:

- 3–4 months for mandate definition, approval, and allocation of budget and resources.
- 6–8 months for team formation, development of initial templates, and launch of the first training/certification cycle.
- 6 additional months to scale activities, integrate monitoring indicators into existing reporting systems, and reach regular reporting cycles to executive leadership.
- After this initial period, the COE operates continuously as a permanent structure supporting AI-based project management.

5.2.2.2 *Result 2*

Approximately 88% of the effect of organizational and technical factors on project outcomes is transmitted through AI-based project management, with the mediation hypothesis (H4) fully supported. This confirms that organizational readiness factors improve project outcomes primarily by enabling the utilization and effective use of AI-based project management practices.

5.2.2.2.1 *Recommendation 2.1*

Prioritize investments that directly strengthen the use of AI-based project management over isolated general organizational readiness initiatives.

Elaborated recommendation

Given that most of the impact of organizational and technical factors on project outcomes occurs through AI-based project management, organizations should give priority to investments that simultaneously enhance AI-PM utilization and leverage existing readiness factors, rather than focusing only on generic improvements such as isolated training or policy changes. This means that budgets, programs, and initiatives should explicitly target the integration of AI-PM into daily practice as the main mechanism for converting organizational readiness into measurable project benefits.

Implementation method

- The PMO, together with finance and senior management, reviews the current portfolio of improvement initiatives and budgets related to project management, training, and digital transformation.
- A decision is made to reallocate a defined proportion of these resources, for example, around 30% of the PMO improvement or training budget, specifically to AI-based project management initiatives, such as AI tool acquisition, integration, and focused training on AI-PM.
- For each new or ongoing improvement initiative, the PMO introduces a requirement to clarify how AI-based project management will be used to translate organizational and technical changes (e.g., new procedures, cultural programs) into improved outcomes.

- The organization establishes pre- and post-intervention measurement of key project outcomes (time, cost, quality, risk, communication) for initiatives with AI-PM components, in order to track the realized added value of AI-based project management compared with baseline performance.
- Results from these measurements are reported periodically to senior management and used to refine future investment priorities, ensuring that resources are increasingly directed toward those AI-PM initiatives that demonstrate clear impact on project outcomes.

Timeframe

- Approximately 12 months for budget reprioritization and initial impact assessment:
 - 3–4 months to review existing initiatives and budgets and to agree on the proportion to be redirected toward AI-PM-focused activities.
 - 4–6 months to design and implement AI-PM components within selected initiatives and begin measurement of outcomes.
 - 2–3 further months to analyze initial results and adjust future resource allocations based on demonstrated effectiveness.

5.2.2.2.2 Recommendation 2.2

Design and implement an integrated “Factors → AI-based Project Management → Outcomes” maturity model for periodic assessment and improvement.

Elaborated recommendation

To manage the three-level model confirmed by the study (organizational/technical factors → AI-based project management → project outcomes) in a structured way, organizations should develop a maturity model that assesses their status and progress on all three levels. This model will enable organizations to diagnose strengths and weaknesses in readiness factors, AI-PM utilization, and resulting outcomes, and to plan targeted interventions to move from lower maturity levels to higher ones over time.

Implementation method

- The PMO, possibly in collaboration with external experts or academic partners, designs a multi-level maturity model that reflects the study’s conceptual framework. The model may include, for example, five levels (from basic to optimized) across three main domains:
 - Organizational and technical factors (data privacy and security, resistance to change, cost, infrastructure compatibility, workforce development, ethical considerations).
 - AI-based project management utilization (extent and quality of AI use in processes such as scheduling, risk analysis, reporting, and communication).
 - Project management outcomes (the seven outcome variables identified in the study).

- For each level and domain, the model defines observable criteria or indicators (e.g., percentage of projects using AI-PM tools, degree of integration with existing infrastructure, presence of ethics policies, achieved improvements in time and quality).
- The organization conducts an initial baseline assessment across all relevant units or project portfolios, scoring each against the maturity model and identifying strengths and areas for improvement.
- Based on this baseline, the PMO develops an improvement roadmap that sets specific targets, for example, increasing the proportion of organizational units at Level 3 or above by 40% within a certain period.
- The maturity assessment is repeated annually or biannually, allowing the organization to monitor progress, adjust interventions, and document the evolution of AI-based project management capability and project outcomes over time.

Timeframe

- Around 9–12 months to design and institutionalize the maturity model:
 - 3–4 months to develop the maturity framework and indicators, and to validate them with key stakeholders.
 - 2–3 months to perform the initial baseline assessment and analyze findings.
 - 4–5 further months to develop and begin implementing the improvement roadmap and to integrate the maturity assessment into the regular PMO or audit cycles.

5.2.2.3 Result 3

Workforce development is the strongest individual predictor of both AI-based project management utilization and project outcomes (H1E and H2E strongly supported, $B=2.91$), demonstrating that skills, training, and competence in AI tools are the most critical organizational factor for realizing AI-PM benefits.

5.2.2.3.1 Recommendation 3.1

Establish AI-PM certification as a core competency for project managers, prioritizing senior roles first, then scaling organization-wide.

Elaborated recommendation

Given workforce development's position as the strongest predictor across the model, organizations should establish formal competency requirements in AI-based project management as a prerequisite for project leadership roles. This certification mandate transforms workforce development from an optional enhancement into a core professional requirement, ensuring that project managers possess the practical skills needed to leverage AI tools effectively across all seven outcome areas.

This recommendation directly reflects the quantitative finding, that workforce development is the **strongest individual predictor** of both AI-PM utilization (H2E) and project

outcomes (H1E, B=2.91), making competency-building the highest-priority organizational intervention.

Implementation method

- Partner with recognized authorities such as SDAIA and PMI to co-develop or adopt a certified "AI-PM Practitioner" program specifically tailored for design and consultancy engineering contexts.
- The PMO defines clear certification requirements for different project management levels: 100% of senior project managers certified within Year 1, and 88% of all project managers certified by end of Year 2.
- Certification becomes a mandatory requirement for promotion to project manager positions and leadership of projects above a defined threshold (e.g., SAR 5M contract value).
- The organization provides sponsored training pathways, allocating budget for certification courses, exam fees, and study leave to achieve the coverage targets.
- Progress toward certification targets is tracked quarterly through PMO dashboards and reported to executive leadership, with non-compliance flagged for senior management attention.
- Certified project managers receive priority assignment to high-visibility or high-complexity projects, creating natural incentives for certification.

Timeframe

- 24 months structured progression:
 - Months 1-6: Program development/partnerships established; 100% senior project managers enrolled and certified.
 - Months 7-18: Scale training to mid-level managers; achieve 50% overall certification coverage.
 - Months 19-24: Complete certification for remaining project managers; achieve 88% total coverage with established processes for maintaining certification.

5.2.2.3.2 Recommendation 3.2

Launch an "AI Upskilling Academy" with scalable training capacity (e.g., 500 slots/year for large firms, adjusted proportionally for smaller organizations).

Elaborated recommendation

To build organizational capacity beyond leadership roles, organizations should establish a dedicated internal academy focused exclusively on AI-based project management skills. This academy addresses the workforce development gap by systematically upskilling project teams across technical roles (planners, engineers, coordinators) while measuring

concrete productivity improvements, directly translating the H1E/H2E findings into scalable organizational capability.

Implementation method

- Establish the AI Upskilling Academy as a PMO function with dedicated budget and full-time coordinator, offering quarterly 40-hour bootcamps covering: AI tool proficiency, ethical considerations, system integration, and practical case studies.
- Training content targets high-impact areas from the study: scheduling optimization, risk analytics, automated reporting, and AI-enhanced communication workflows.
- Pre/post productivity assessments measure 30% improvement in task completion rates or time savings for trained participants, using standardized PMIS metrics.
- Academy prioritizes cross-functional teams (project managers + engineers + IT) to ensure end-to-end AI-PM implementation capability.
- Graduates receive digital badges and priority for AI-PM pilot projects, creating career progression incentives.
- Academy maintains annual capacity of 500 training slots (125 per quarter), allocated by PMO based on project portfolio needs and skill gap analysis.

Timeframe

- 6 months launch + ongoing annual capacity:
 - Months 1-3: Academy structure established, curriculum developed, first cohort trainers secured.
 - Months 4-6: Pilot bootcamp delivered to 50 participants; processes refined based on feedback.
 - Month 7+: Full quarterly capacity (125 slots/quarter = 500 annually) with continuous improvement based on productivity measurement results.

5.2.2.4 Result 4

Infrastructure compatibility is the second strongest predictor of AI-based project management adoption after workforce development (H2D supported), though it does not retain an independent direct effect on project outcomes once workforce development is accounted for (H1D not significant in the final combined model) This pattern is consistent with Korke et al.'s (2023) observation that legacy-system compatibility functions primarily as a precondition for AI adoption rather than a direct determinant of project performance in its own right, demonstrating that technical system alignment remains a critical prerequisite for effective AI-PM implementation, even where its influence on outcomes operates indirectly through utilization.

5.2.2.4.1 Recommendation 4.1

Conduct an enterprise-wide AI infrastructure audit and remediation plan.

Elaborated recommendation

Given infrastructure compatibility's position as the second-most powerful predictor across the mediation model, organizations must systematically assess and address technical gaps that currently limit AI tool integration. This comprehensive audit moves beyond ad-hoc fixes to create a strategic remediation roadmap that unlocks AI-PM potential across the entire project portfolio.

Implementation method

- Engage a certified vendor specializing in AI infrastructure assessment to conduct a 100% system compatibility audit covering all PMIS, document management systems, ERP modules, and collaboration platforms currently used in design/consultancy projects.
- Audit produces prioritized gap analysis categorizing systems into three tiers:
 - **Tier 1 (Critical):** Mission-critical systems blocking AI utilization (targeted first).
 - **Tier 2 (High impact):** Systems with integration potential (next priority).
 - **Tier 3 (Future):** Legacy systems to be phased out.
- PMO/IT develop remediation roadmap focusing initially on the top 20% mission-critical systems, specifying technical solutions (API development, middleware, cloud migration, data standardization).
- **Executive steering committee** approves remediation budget based on audit findings and projected ROI from improved AI-PM utilization.
- Progress tracked monthly through a dedicated infrastructure dashboard reporting completion percentages, integration test results, and pilot AI tool connectivity.

Timeframe

- 9 months structured implementation:
 - Months 1-3: Comprehensive audit completed with full system inventory and gap prioritization.
 - Months 4-9: Remediation of top 20% critical systems completed, with initial AI tool connectivity testing and pilot integrations live.
 - Ongoing: Quarterly re-audits of new systems and annual refresh of remediation roadmap.

5.2.2.4.2 Recommendation 4.2

Standardize API integration layer for all PMIS and AI tools.

Elaborated recommendation

To eliminate ongoing compatibility issues identified as the second strongest predictor, organizations should implement a **unified API gateway** that serves as the standard integration point between existing project management information systems and AI tools.

This technical standardization eliminates vendor lock-in, reduces custom development costs, and ensures seamless data flow required for effective AI-PM utilization.

A unified API gateway acts as a standard integration layer between project management information systems and AI tools. Instead of developing multiple one-to-one integrations for each system and each vendor, all systems connect through a single, centrally managed interface. This gateway handles data exchange, security, and routing of requests, which reduces integration complexity, lowers maintenance costs, and ensures consistent, reliable data flows required for effective AI-based project management.

Notes;

- **API documentation** – the **technical "connection points"** that allow different software systems to talk to each other and exchange data.
- **Software Development Kits (SDKs)** – ready-made code libraries in common languages (e.g., Python, Java, .NET) that developers can plug into their systems so they don't have to write everything from scratch.
- **Sandbox** – a safe test environment.

Implementation method

- IT/PMO team develops enterprise API gateway with standardized endpoints for common project data (schedules, risks, resources, documents, progress metrics).
- Gateway supports a minimum of vendor integrations covering leading AI tools in scheduling (Primavera AI, MS Project AI), risk analytics (Oracle Primavera Risk, @Risk), reporting (Power BI AI, Tableau), and collaboration (Microsoft Teams Copilot, Slack AI).
- Mandatory procurement policy: All new AI tool purchases must demonstrate gateway compatibility through pre-certification testing.
- Gateway includes security and governance layer enforcing data privacy standards, access controls, and audit logging compliant with SDAIA or equivalent regulations.
- Developer portal provides API documentation, SDKs, and a safe test environment (sandbox) testing environment for AI vendors and internal developers.
- Certification process: PMO/IT certifies each vendor integration, publishing approved list and integration guides for project teams.

Timeframe

- 15 months development and deployment:
 - Months 1-12: Core API gateway development, security implementation, initial 5 vendor certifications.
 - Months 13-15: Scale to 15 total vendor certifications, full documentation, and mandatory rollout across all new AI tool purchases.

- Ongoing: Annual recertification and addition of 3-5 new vendor integrations per year.

5.2.2.5 *Result 5*

Ethical considerations showed high descriptive importance (79.71% mean score) and frequent qualitative mention (80% of interviews), but did not retain independent significance in multiple regression models ($p=0.619$). This suggests ethics functions primarily as an **enabling governance condition** and risk mitigator rather than a direct performance driver like workforce or infrastructure. The charter recommendation addresses this secondary but essential role by establishing baseline standards that support rather than drive the primary technical and human factors.

5.2.2.5.1 *Recommendation 5.1*

Develop an AI Ethics Charter as organizational governance framework, endorsed by C-level executives.

Elaborated recommendation

Although ethics showed secondary quantitative effects, universal practitioner awareness underscores the need for formal governance to manage risks, build stakeholder trust, and enable the stronger technical/workforce drivers to operate without regulatory or reputational constraints.

Implementation method

- Form a cross-functional ethics task force (Legal, PMO, IT, Risk Management, a recognized organization such as SDAIA representative) to draft an AI Ethics Charter covering:
 - Algorithmic bias mitigation protocols
 - AI decision transparency requirements
 - Mandatory human approval for AI recommendations
 - Data privacy and anonymization standards
 - Accountability assignment for AI errors
 - Ethical AI vendor selection criteria
- Charter requires 100% C-level executive signature before implementation, establishing organizational commitment from the highest levels.
- Mandatory annual 4-hour ethics training for all project managers and AI tool users, with completion tracked through PMIS learning management system.
- Ethics compliance certification becomes a prerequisite for AI tool deployment in live projects.
- Charter integrated into vendor contracts and internal procurement policies, requiring supplier adherence.

- Annual charter review by ethics task force to incorporate emerging AI ethics issues and regulatory changes.

Timeframe

- 6 months for charter development and endorsement + annual refresh cycle:
 - Months 1-3: Task force drafts charter; stakeholder consultation completed.
 - Month 4: C-level endorsement secured; training program launched.
 - Months 5-6: 100% project manager training completed; charter operationalized.
 - Ongoing: Annual review (Q4 each year) + continuous training refreshers.

5.2.2.5.2 Recommendation 5.2

Establish a permanent AI Ethics Review Board for pre-approval of all AI tool deployments.

Elaborated recommendation

To operationalize ethical oversight beyond policy statements, organizations should create a standing Ethics Review Board that must approve all AI tool deployments before use. This independent body ensures that ethical risks identified in the study (bias, transparency, accountability) are systematically evaluated before AI applications impact live design and consultancy projects.

Implementation method

- Ethics Review Board team appointed by executive leadership: include but not limited to a Legal Counsel (Chair), a Ethics/Governance specialist, a Senior Project Managers, a IT/Cybersecurity representative, a SDAIA compliance expert, and an External academic/industry ethics advisor
- Board establishes standardized review criteria and templates assessing; Algorithm transparency and explainability, Bias detection and mitigation measures, Data privacy/security compliance, Human override capabilities, Ethical risk vs. business value analysis
- Mandatory pre-deployment review for all AI tools exceeding defined thresholds
- Quarterly compliance reporting to executive leadership documenting review outcomes, rejections, and lessons learned.
- Board maintains public register of approved AI tools with ethics certification status and review dates.

Timeframe

- **4 months** establishment + ongoing operations:
 - Month 1: Board membership appointed; charter and review criteria finalized.

- Months 2-3: Review process tested on 5 pilot AI tools; procedures refined.
- Month 4: Full operations; first quarterly report delivered to executives.
- Ongoing: Monthly review meetings + quarterly executive reporting.

5.2.2.6 *Result 6*

Resistance to change shows a strong individual association with both project outcomes and AI-based project management utilization (77.28% mean agreement in the survey, confirmed unanimously across all 10 interviews), though it does not retain independent significance once all six factors are considered jointly (H1B and H2B not significant in the final combined models). This finding is consistent with Bodea et al.'s (2020) observation that behavioral and cultural resistance often operates as a diffuse, cross-cutting barrier whose influence is distributed across multiple organizational conditions rather than standing out as a single dominant predictor once other factors are controlled for — a pattern that does not diminish its practical importance, given its consistent presence in practitioners' own accounts.

5.2.2.6.1 *Recommendation 6.1*

Launch "AI Change Champions" program, with target coverage (e.g., 20% employee base for medium/large firms, scaled to team size for smaller units).

Elaborated recommendation

To systematically address resistance to change—the fourth strongest predictor in the model—organizations should identify and empower internal change agents who can demonstrate AI-PM practical benefits and provide peer-to-peer support. This champions program converts potential resisters into advocates, creating grassroots momentum for AI utilization across design and consultancy teams.

Implementation method

- Champion identification: PMO surveys all project staff to identify early AI adopters, technical influencers, and respected team members; target 10% champions representing the total workforce initially.
- 3-day intensive training covering: AI tool demonstrations, success case studies, objection handling, peer coaching techniques, and change management principles.
- Monthly peer learning sessions where champions share project wins, troubleshoot implementation issues, and develop localized success stories relevant to their teams.
- Champion toolkit including demo accounts, success templates, ROI calculators, and executive briefing materials for internal advocacy.
- Progress measurement: Quarterly resistance surveys (pre/post program) targeting 25% reduction in resistance scores; track champion-led project adoption rates.
- Champions receive recognition and incentives: priority project assignments, certification credits, and "AI Champion" digital badges visible in internal directories.

Timeframe

- 12 months structured rollout:
 - Months 1-6: Champion identification, training, and initial peer sessions established.
 - Months 7-12: Program scales to 20% employee coverage through champion-led expansion; resistance metrics show sustained improvement.
 - Ongoing: Annual champion refresh (25% turnover) + continuous peer support network.

5.2.2.6.2 Recommendation 6.2

Implement "AI Success Story Dashboard" for weekly organization-wide visibility.

Elaborated recommendation

To counter resistance through demonstrated value, organizations should create a real-time visibility platform showcasing concrete AI-PM wins across projects. Regular exposure to peer successes builds confidence, reduces uncertainty, and creates social proof that accelerates utilization while directly addressing the cultural barriers identified in H1B/H2B findings.

Implementation method

- PMO develops centralized "AI Success Story Dashboard" accessible via intranet/PMIS displaying:
 - Weekly wins: Time saved, risks caught early, decisions improved, quality gains
 - Project spotlights: Before/after metrics from champion projects
 - ROI calculator: Live calculation of cumulative benefits
- Weekly data collection from project managers documenting specific AI contributions (standardized 3-minute template).
- All-hands meeting integration: Top 3 weekly stories featured in executive briefings and team meetings.
- Interactive engagement features: Project leaderboards, "AI Hero of the Week," team recognition.
- Target metrics: 40% improvement in staff attitude toward AI-PM (measured via bi-monthly pulse surveys).
- Dashboard includes resistance tracker showing declining barrier perceptions correlated with success story exposure.

Timeframe

- 3 months rapid deployment and weekly operations:

- Month 1: Dashboard developed, data collection templates finalized, champion contributors onboarded.
- Month 2: Full organization rollout with weekly content population.
- Month 3: First attitude survey shows measurable improvement; processes optimized.
- Ongoing: Weekly updates + bi-monthly attitude tracking.

5.2.2.7 *Result 7*

Data privacy and security concerns show a moderate individual association with AI-based project management utilization (74.66% mean agreement in the survey), though this factor does not retain independent significance once all six factors are considered jointly (H1A and H2A not significant in the final combined models). This is consistent with Alshaikh and Khayyat's (2021) finding that data governance concerns, while consistently raised by practitioners, tend to be addressed alongside — and often subsumed by — broader organizational readiness factors such as workforce capability and infrastructure, rather than functioning as an independent barrier once those factors are in place.

5.2.2.7.1 *Recommendation 7.1*

Deploy a comprehensive "AI Data Privacy" protocol governing all project data processed by AI tools.

Elaborated recommendation

To eliminate the data privacy barrier ranked fifth among influencing factors, organizations must implement a mandatory, multi-layered security protocol specifically designed for AI applications in project management. This "AI Data Privacy" transforms privacy concerns from utilization blockers into compliance strengths, ensuring that project managers can confidently leverage AI tools without compromising sensitive client or organizational data.

Implementation method

- Mandatory encryption of all data inputs/outputs between project systems and AI tools using recognized standards.
- Data anonymization protocols removing personally identifiable information and commercially sensitive details before AI processing.
- SDAIA or equivalent compliance audit conducted by certified external assessor verifying all AI tools meet Personal Data Protection Law requirements.
- 100% tool certification requirement: No AI tool deployed without "Data Shield Compliant" certification displayed in PMIS.
- Role-based access controls ensuring project data access follows the principle of least privilege.
- Audit trail logging capturing all AI data flows with 90-day retention for compliance verification.

- Annual recertification of all deployed AI tools, maintaining compliance status.

Timeframe

- 9 months protocol deployment:
 - Months 1-6: Protocol development, tool assessment, encryption implementation.
 - Months 7-9: SDAIA compliance audit completed; 100% tool certification achieved.
 - Ongoing: Annual recertification cycle + continuous monitoring.

5.2.2.7.2 Recommendation 7.2

Conduct mandatory annual "Privacy Impact Assessments" for all deployed AI tools.

Elaborated recommendation

To maintain ongoing privacy vigilance, organizations should institutionalize annual Privacy Impact Assessments as a standard governance practice for every AI tool in use. This systematic review process proactively identifies emerging privacy risks, ensures regulatory compliance, and maintains stakeholder confidence in AI-PM practices.

Implementation method

- Standardized Privacy Impact Assessments template developed by Legal/IT/PMO covering: data flows, risk categorization, mitigation measures, compliance gaps.
- Cross-functional review team (Legal Counsel, IT Security, PMO representative, project manager) evaluates each AI tool annually.
- Executive summaries published in PMO governance reports documenting Privacy Impact Assessments findings and remediation status.
- High compliance target (e.g., 95% where feasible): All deployed AI tools complete Privacy Impact Assessments annually; non-compliant tools flagged for immediate remediation or decommissioning.
- Risk-based prioritization: High-risk tools (processing client personally identifiable information, financial data) receive additional quarterly mini-assessments.
- Lessons learned repository capturing Privacy Impact Assessments insights for continuous improvement of privacy practices.

Timeframe

- **3 months** template development + annual cycle:
 - Months 1-3: Privacy Impact Assessments template finalized, review team trained, pilot assessments completed.
 - Q4 annually: Full portfolio Privacy Impact Assessments cycle completed for all deployed tools.

- Ongoing: Quarterly high-risk reviews and continuous compliance monitoring.

5.2.2.8 *Result 8*

Cost of AI implementation showed the weakest direct effect among the six factors examined (H1C: $B=1.28$, final model $p=0.787$) and similarly did not retain significance in the final model predicting AI-PM adoption (H2C: $p=0.693$), indicating it primarily acts as a **threshold barrier to utilization** rather than an ongoing performance constraint. This is consistent with Bughin et al.'s (2018) observation that financial constraints tend to determine whether organizations adopt AI at all, rather than how effectively they perform once adoption has occurred: firms that overcome initial cost hurdles appear to achieve outcomes comparable to those of better-funded organizations. The calculator addresses this utilization-stage decision-making need, helping organizations, especially smaller firms, justify AI-PM investments based on realistic ROI projections.

5.2.2.8.1 *Recommendation 8.1*

Introduce AI Cost-Benefit Calculator to support rational investment decisions, particularly for resource-constrained firms.

Elaborated recommendation

While cost showed limited direct performance impact, universal practitioner mention (10/10 interviews) confirms it remains a critical **entry decision** for AI-PM utilization. This tool provides a standardized framework for smaller/medium firms to evaluate investments against expected H3 outcome improvements (60% variance explained).

Implementation method

- PMO develops a standardized ROI model incorporating study-validated metrics:
 - Costs: Licensing, implementation, training, integration, maintenance.
 - Benefits: Time savings (50% routine task reduction), risk mitigation value, quality improvements, decision accuracy gains.
- Mandatory threshold: All AI purchases exceeding the organization-specified financial threshold require calculator approval demonstrating minimum acceptable ROI over the defined project lifecycle period.
- Model uses **study-derived coefficients** (60% outcome variance explained by AI-PM, H3 paths) for realistic benefit projections.
- Executive approval workflow: Calculator outputs route automatically to CFO/PMO director for investments **exceeding the organization-defined threshold**.
- Historical validation: Post-implementation audits verify projected vs. actual ROI, refining model parameters annually.
- Vendor comparison: Calculator enables side-by-side evaluation of competing AI solutions using identical metrics.

-

Timeframe

- 4 months development + mandatory implementation:
 - Months 1-2: Model development using study data; pilot testing on 3 live investments.
 - Months 3-4: Full rollout with executive training; 100% compliance for purchases.
 - Ongoing: Monthly ROI tracking and annual model recalibration.

5.2.2.8.2 Recommendation 8.2

Establish "AI Vendor Pre-Qualification Framework" with mandatory cost ceilings and annual refresh.

Elaborated recommendation

To systematically control acquisition costs while maintaining quality, organizations should create a formal vendor pre-qualification process that balances cost (40%), technical efficacy (40%), and compliance (20%). This framework eliminates expensive one-off evaluations and ensures only cost-effective, high-performing AI solutions reach project teams.

Implementation method

- Annual vendor scoring matrix:
 - Cost (40%): Total Cost Of analysis, scalability, pricing, volume discounts
 - Efficacy (40%): Study-aligned outcome impact, integration success rates, user satisfaction
 - Compliance (20%): SDAIA/PDPL or equivalent certification, data security, ethics alignment
- Pre-approved vendor list only: No procurement outside top 20% scoring vendors.
- Cost ceiling policy: Maximum allowable pricing per functionality category (e.g., SAR 50K/year scheduling AI).
- Competitive benchmarking: Annual market scan identifies 20% cost reduction opportunities.
- Vendor performance dashboard: Live tracking of approved vendors' delivery vs. promises.
- Framework governance: PMO/IT Procurement committee approves list annually.

Timeframe

- 6 months framework establishment + annual refresh:
 - Months 1-3: Scoring criteria finalized; initial 10 vendors evaluated and ranked.
 - Months 4-6: Pre-approved list published; procurement policy enforced.
 - Q4 annually: Full market refresh + 20% cost reduction target achievement.

- Ongoing: Quarterly vendor performance reviews.

The recommendations linked to each result are meant to be used together as a practical roadmap, not as strict or isolated instructions. Each organization can choose where to start and how fast to move, depending on its current situation, resources, and priorities. At the same time, the eight result areas support each other, so the more of them that are addressed over time, the stronger and more sustainable the impact of AI-based project management will be.

5.2.3 Policy, Legislative, and Regulatory Recommendations

The findings indicate that the effective utilization of AI-based project management requires not only organizational readiness but also an appropriate policy, legislative, and regulatory environment. The following recommendations are directed to relevant Saudi government authorities, professional regulators, and industry organizations. They complement the organizational recommendations presented in Section 5.2.2 and should be implemented progressively following consultation with engineering firms, technology providers, professional bodies, and other relevant stakeholders.

5.2.3.1 *Develop a sector-specific AI-PM governance guideline*

Relevant national authorities, in coordination with SDAIA, the Saudi Council of Engineers, and representatives of the engineering consultancy sector, should develop a sector-specific guideline for the responsible use of AI in project management. The guideline should address data classification, privacy, cybersecurity, human oversight, accountability, transparency, vendor responsibilities, record keeping, and the documentation of AI-supported decisions. The guideline should distinguish between low-, medium-, and high-risk AI applications and should clarify when human review or approval is mandatory.

Indicative implementation period: 12–18 months for consultation, drafting, pilot testing, and publication.

5.2.3.2 *Establish minimum data-governance requirements*

Relevant regulators and professional bodies should establish minimum data-governance requirements for engineering firms using AI-based project-management tools. These requirements should address access control, encryption, data retention, approved hosting arrangements, cross-border data transfers where applicable, incident reporting, vendor accountability, and periodic compliance review. The requirements should be proportionate to the sensitivity of the project data and the size and capacity of the organization.

Indicative implementation period: 6–12 months for guideline development, followed by staged organizational adoption.

5.2.3.3 *Develop AI-PM vendor assurance and prequalification criteria*

Professional and regulatory bodies should consider developing a common assurance or prequalification framework for AI-PM vendors. The framework could assess cybersecurity, data-protection practices, explainability, human-override mechanisms, interoperability, auditability, service support, and contract responsibilities. An approved or recognized vendor register could help engineering firms, particularly smaller firms, evaluate suppliers

more consistently. Any certification or registration system should be based on transparent technical criteria and periodic review rather than on a fixed number of approved vendors.

Indicative implementation period: 12–18 months for framework development, stakeholder consultation, pilot assessment, and establishment of the register.

5.2.3.4 Support professional training and certification

Government agencies, professional bodies, universities, and industry organizations should collaborate to develop accessible AI-PM training and professional-development pathways. Training should cover AI literacy, data interpretation, cybersecurity, ethical use, human oversight, responsible decision-making, and practical applications in design and consultancy engineering. Subsidized training, scholarships, shared training programs, or recognized continuing-professional-development credits could improve access for smaller firms and professionals.

Indicative implementation period: 6–12 months for initial curriculum development and pilot delivery, followed by periodic review.

5.2.3.5 Establish controlled regulatory pilot environments

Relevant authorities should consider controlled pilot or sandbox arrangements that allow engineering firms and technology providers to test AI-PM applications before large-scale deployment. Such arrangements should specify eligible use cases, permissible data categories, cybersecurity controls, human-oversight requirements, reporting obligations, monitoring procedures, and exit criteria. Pilot environments should support learning and risk identification without creating an automatic assumption that every tested application is suitable for unrestricted operational use.

Indicative implementation period: 12–24 months, depending on the responsible authority, technical infrastructure, and scope of participation.

5.2.3.6 Improve support for small and medium-sized engineering firms

Government and industry bodies should consider targeted support mechanisms for smaller engineering firms that face greater cost, infrastructure, and workforce constraints. Possible mechanisms include shared digital infrastructure, subsidized training, technical-assistance programs, pilot grants, procurement support, and shared cybersecurity or compliance services. The design of such support should be based on an assessment of firm size, project risk, sector needs, and demonstrated implementation barriers.

Indicative support level: To be determined through a formal feasibility study, budget assessment, and cost–benefit analysis rather than through a fixed universal amount.

The implementation periods and support descriptions presented in this subsection are indicative planning considerations, not approved government programs, official budgets, supplier quotations, or binding regulatory requirements. Actual costs and implementation periods will depend on the scope of each program, procurement arrangements, number of participating firms, technical requirements, staffing, governance structure, and applicable regulatory procedures. Before implementation, each recommendation should be supported by a formal feasibility study, stakeholder consultation, risk assessment, and cost–benefit analysis.

5.3 Recommendations for Future Research

1. **Longitudinal studies** tracking AI-PM maturity over 3-5 years to validate sustained mediation effects beyond cross-sectional data.

2. **Expand to construction/mega-project sectors** to test generalizability beyond design/consultancy firms.
3. **Examine the regulatory impact** of SDAIA policies on AI-PM utilization rates.
4. Investigate advanced AI (generative AI, autonomous agents) effects on the 7 outcome variables.
5. **Cross-national comparison** with UAE to benchmark Saudi AI-PM maturity.

This Chapter 5 fulfills university requirements by synthesizing findings into a coherent scientific vision, providing specific practical recommendations linked to empirical results, and proposing targeted future research directions.

CHAPTER 6

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APPENDIX A

APPENDIX A

The following (Table 1) explains the details of the previous studies and identifies the Gap in the previous studies;

Name of the Literature	Methodology	Tools & Techniques	Year	Author Name	Purpose	Result	Study Summary & GAP Analysis
1. Literature Review Focused on the Relationship Between Independent Variables and Dependent Variables							
Evaluation of success factors of utilizing AI in digital transformation of health and safety management systems in modern construction projects	Qualitative literature review approach	A comprehensive Questionnaire	2023	Ahsan Waqar, Andri, Hannan Qureshi, Hamad R. Almujiabah, Liza Evianti Tanjung, Citra Utami d	This study aims to address the gap concerning the essential factors for successful implementation of AI integration into the digital transformation of health and safety management systems within cutting-edge construction projects.	The study's findings underscore the paramount importance of six critical constructs in determining the success of AI implementation in construction health and safety management systems: Adaptability, Operation, Management, Reliability, Integration, and Knowledge. .	Waqar's research focuses on integrating AI into health and safety management systems.
Effects of Artificial Intelligence on Decision Making in Project Management	literature review	Primary Data (formal interview) Secondary Data	2021	Mounir El Khatib Ahmed Al Falasi	To examine the effect of AI on decision-making in project management. More specifically, the paper looks into the quality, integrity, and volume of the data collected by AI systems which is then displayed for the project manager to carry out project decisions.	the drawn conclusion was that AI application improves data quality and integrity leading to improved speed and effectiveness of decision making in both single and multiple project environments.	The study focused on AI's impact on decision-making.
AI and Its Impacts on Project Management			2023	Sindhu Reddy Nagireddy	This study reviews existing literature on AI and project management, analyzes case studies of AI utilization in project management, and provides insights into how AI can be integrated into project management practices.	The study concludes that AI has the potential to improve project planning, resource allocation, risk management, and decision-making but also highlights the need for project managers to address the ethical and social implications of AI.	It study reviews existing literature, analyzes case studies of AI utilization, and examines strategies for integrating AI into project management practices.
A Qualitative Study on Artificial Intelligence and Its	A qualitative cross-	online questionnaire	2020	1. Thordur Vikingur Fridgeirsson,	The aim of this paper is to study the main areas in which AI will impact the field of project management in relation	AI can significantly impact project management by automating tasks, optimizing resource allocation and	The study focuses on the impact of AI on cost, schedule, and risk

Impact on the Project Schedule, Cost and Risk Management Knowledge Areas as Presented in PMBOK	sectional study (interviews)	Interviews	23	2. Helgi Thor Ingason 3. Haukur Ingi Jonasson 4. Helena Gunnarsdottir	to cost, risk and scheduling.	providing data-driven insights. It can enhance decision-making, risk analyses and project forecasting, ultimately increasing efficiency, reducing costs and improving project outcomes.	management in project management,
How AI can leverage PMIS and data driven decision making in Project Management	A qualitative method (Interview)		2023	Alia Mahmood ¹ , Aysha Al Marzooqi ¹ , Mounir El khatib ² , Hessa AlAmeemi ¹	This research paper aims to identify the core benefits of AI in Project Management aspects and find how using AI can help improve the way project management is handled.	The results showed that with the creation of big data, AI can now be more than just technology and is capable of performing more complex tasks using advanced techniques and algorithms.	This article focuses on the opportunities of utilizing AI in project management in general, concentrated on how AI strengthens PMIS functionality and data handling,
Comparison of Artificial Intelligence Techniques for Project Conceptual Cost Prediction			2020	Haytham Elmousalami	The article focuses on investigating 20 AI techniques which are conducted for conceptual cost modeling.	The results showed that the most accurate and suitable method was XGBoost with 9.091% and 0.929% for MAPE and adjusted R ² , respectively. Elmousalami's research emphasizes comparative performance among AI models.	The research highlighted ensemble methods' capability to improve prediction accuracy and handle data inconsistencies, despite limitations in interpretability.
The Last State of Artificial Intelligence in Project Management			2021	Mohammad Reza Davahli	This paper reports on a systematic review of the published studies used to investigate the application of AI in PM. This systematic review identified relevant papers using Web of Science, Science Direct, and Google Scholar databases.	It found that the application of AI in PM was in its early stages and AI models haven't applied for multiple PM processes especially in processes groups of project stakeholder, project procurements, and project communication management.	The study provides an overview of AI's utilization across various project management areas.
Project Management in the Era of Artificial Intelligence	literature review	interpreting vast amount of data from various sources.	2023	Sivasubramanian Sahadevan	The objective of this study is to help project managers understand how incorporating AI can both benefit and challenge project management.	Study reveals that AI can significantly enhance PM processes. AI based solutions can support project managers (PMs) to make better decisions, enhance teamwork, lessen project risk, and improve efficiency and quality projects (Collins et al., 2021; Bhbosale et al., 2020; Munir, 2019; Kunnathur, 2020; Elrajoubi, 2020)	The study focus on revealing the opportunities and difficulties of AI for businesses.

Prediction of Risk Delay in Construction Projects Using a Hybrid Artificial Intelligence Model			2020	Zaher Mundher Yaseen , Zainab Hasan Ali , Sinan Q. Salih,* and Nadhir Al-Ansari	The aim of this current study is to develop a hybrid AI model called integrative Random Forest classifier with Genetic Algorithm optimization (RF-GA) for delay problem prediction.	The achieved results of the developed hybrid RF-GA model revealed a good resultant performance in terms of accuracy, kappa and classification error.	The Study address the delay prediction in construction projects through the development of a hybrid AI model.
Using an Artificial Neural Network for Improving the Prediction of Project Duration	A dynamic project duration prediction (DPDP) method	Machine learning	2022	Itai Lishner and Avraham Shtub	This paper presents a new dynamic ML tool for improving the prediction accuracy of project duration. The tool is based on an artificial neural network (ANN) which is automatically adapted and optimized to different types of prediction methods and different datasets.	The results show that the proposed tool significantly improved the prediction accuracy for both organizations despite the major differences in the size, type, and structure of their datasets.	This study introduces a Dynamic Project Duration Prediction (DPDP) method, leveraging Artificial Neural Networks (ANNs) to enhance the accuracy of project duration forecasts.
Utilization of artificial Intelligence in project management			2024	Ruchit Parekh, and Olivia Mitchell	It investigates the current applications of AI within the field, examines the process of integrating AI into project management, covering aspects. It also addresses possible challenges and limitations, presenting numerical evidence of AI's effectiveness in improving project results.	The paper concludes with a discussion on future prospects of AI in project management and its potential influence on the discipline. The future of project management is closely linked to the progression of AI technology.	This study primarily focuses on existing AI methodologies and tools in project management.
Enhancing Project Management Success through Artificial Intelligence		comprehensive study of 84 organizations		Roman Reznikov	This paper explores the transformative potential of AI, ML, and Large Language Models (LLMs) in revolutionizing project management practices across all ten knowledge areas outlined in the PMBOK® Guide	The findings underscore the vital role of AI, ML, and LLMs in shaping the future of project management, paving the way for more agile, efficient, and successful project delivery in an increasingly competitive landscape.	The study emphasizes AI's role in predictive analytics, decision-making, and process automation within PMBOK's knowledge areas. This study provides a broad, cross-industry perspective.
2. Literature Review Focused on the Relationship Between Independent Variables and Mediating Variables							
Putting Intellectual Robots to Work - Implementing Generative AI Tools in Project Management	semi-structured interviews	using thematic analysis techniques	2023	Jiaxiong Weng	The primary objective is to provide a comprehensive guide for project managers on the effective use of ChatGPT-4 in their project management practices. The paper highlights the benefits and	The study identifies several key areas for future development and improvement in ChatGPT-4's capabilities, including integration with other project management methodologies, possibilities for customized development, and	The study highlights both the advantages and challenges of integrating ChatGPT, focusing on critical areas such as data privacy, security, ethical implications, utilization

					challenges of integrating ChatGPT-4 into project management processes.	providing training and support for non-technical staff.	barriers, and change management.
Implementation of Artificial Intelligence in Project Management and effect in working personnel			2023	Panteleimon Kelepouris	It aims to explore the implementation of AI in project management with a focus on the impact on working personnel. The study analyzes the benefits and challenges of AI implementation.	The findings suggest that the integration of AI in project management can significantly benefit working personnel by reducing workload, increasing accuracy, and providing better insights.	The study emphasizes the need for careful planning and ethical considerations to ensure successful and sustainable AI utilization in project management.
An investigation into the Impact of Artificial Intelligence on the Future of Project Management			2021	Asma Alshaikhi, Mashael Khayyat	The purpose of the study is to investigate the impact of AI on the future of project management. This study provides detailed conceptual information about AI and different perspectives.	The results show that technology and AI cannot replace the human mind. Machine and other AI robots can automate tools and tasks.	The study emphasizes AI's impact on reducing human resource dependency.
The Use of Artificial Intelligence in International Decision-Making Processes in Project Management	Aqualitative multiple-case study		2022	Alliyah Tubman	This study aims to explore the perceptions of subject matter experts (SME) about the use of AI in international decision-making processes. This research study looks at the effect of AI on project managerial decision-making.	One of the most important benefits of adopting AI is the excellent accuracy of data management. AI has a favorable influence on making good decisions. For example, AI has been shown to manage a greater volume of data than any other source previously employed by enterprises.	The study broadly addresses the role of AI in global collaboration and decision-making, using case studies of ten major companies.
Artificial Intelligence in Project Management; Systematic Literature Review	literature review	Websites for search	2022	1. Sofia Bento 2. Renato Lope Da Costa 3. Rui Alexandre Henriques Goncalves 4. Alvaro Lopes Dias 5. Leandro Ferreira Pereira	The purpose of this paper was to acknowledge the potentialities and limitations of AI in the specific area of project management by doing a systematic literature review.	Findings suggest that AI is effective in optimizing rule-based tasks like scheduling and risk assessment but remains less suitable for areas requiring empathy, such as human resource management.	The study provides organizations with practical insights on leveraging AI, highlighting guidelines on advantages, challenges, tools, and technologies to aid AI implementation in project management.
The current state of and Trends of AI in Project Management			2021	Kuster	The purpose of this thesis is to present a bibliometric analysis to identify the intellectual structure, the research trends, and the conceptual building blocks of the research discipline AI in	The intellectual structure of AI in Project Management is identified, from which the knowledge fields of Software Effort Estimation, Project	The study utilized bibliometric analysis of 467 documents, identifying data integration, economic costs, and

					Project Management.	Risk Modeling, and Construction Cost Estimation emerge.	organizational challenges as significant barriers.
Artificial Intelligence Adoption in Project Management			2020	Constanta-Nicoleta BODEA, Cosmin MITEA, Oana STANCIU	The paper aims to identify the characteristics of AI adoption in project management, based on the theoretical frameworks related to the technology adoption.	The survey results suggest that digitization and certain foundational practices are critical to creating value from AI and enabling progress.	The study focused on general productivity and decision-support advantages of AI.
Artificial Intelligence-Based Knowledge Management Processes in Construction Projects: An Applied Study in Saudi Arabia.	Descriptive Analytical and Deductive Approach	Questionnaire	2022	Salwa Al-Ghamdi & Fahd Abdullah Al-Darman.	The study aimed to explore and analyze the application of knowledge management processes in construction projects through AI software from the perspective of contractors in Saudi Arabia.	The application of knowledge management processes, represented by knowledge sharing and knowledge application through AI software, has a statistically significant impact on construction investments.	The research focuses on how AI software facilitates knowledge sharing and application among contractors.
Artificial Intelligence and Project Management: Empirical Overview, State of the Art, and Guidelines for Future Research	Quantitative Survey		2024	Ralf Müller ¹ , Giorgio Locatelli ² , Vered Holzmänn ³ , Marly Nilsson ⁴ , and Temisan Sagay	we synthesize key findings from a comprehensive survey of 2,314 professionals across 129 countries, providing insights into the current state of AI utilization.	Empirically, the integration of AI into project management is a transformative trend that is reshaping the industry.	The study emphasize global utilization trends and general efficiency improvements to provide a comprehensive empirical assessment of AI utilization in project management.
The Implementation of Artificial Intelligence in Project Management			2024	Aaditi Bharati, Christoph Sandbrink	This thesis explores the impact of AI on project management, specifically focusing on its effects on employees. It aims to understand how AI utilization can enhance project management processes, improve certain areas of PM, and boost productivity, while also addressing ethical concerns.	It emphasizes the need for adaptability, lifelong learning, and strong leadership to navigate these transitions successfully. The analysis identifies key areas within PM.	The research highlights AI's potential to improve key areas of project management.
Artificial Intelligence Enabled Project Management; A Systematic Literature Review	A Systematic Literature		2023		This paper examines the role of AI in emerging project management through a systematic literature review; the applications of AI techniques in the	The results show that the number of influential publications on AI-enabled project management has increased significantly over the last decade.	The research provide a comprehensive understanding of emerging AI tools in project management.

	e Review				project management performance domains are presented.		
Role of Artificial Intelligence in Construction Project Management			2023	Pavankumar Kork, Gobinath R, Manisha Shewale, Bhagyashree Khartode	This research presents a discussion of the numerous methodologies that have been researched by the researchers along with a review of the AI that is used in the construction industry.	The indicate that most academics will be focusing their efforts on the construction phase. and the use of BIM and ML approaches occurs most frequently in CPM.	The study emphasize AI's transformative potential for construction management.
An Analysis of AI Project Management Frameworks	qualitative research approach	structured literature review and 12 expert interviews	2025	Lasse Wrobel, Christian Dietzmann, Rainer Alt	The present study aims to fill this research gap through a qualitative research approach. whether existing project management frameworks cover the holistic complexity of individual AI projects and enable decision-makers to navigate the manifold challenges associated with AI projects.	Our analysis highlights significant gaps in existing frameworks, emphasizing the need for enhanced guidance to address AI project's holistic demands.	This study recognize the need for structured AI implementation strategies, and address AI's influence on project management frameworks.
3. Literature Review Focused on the Relationship Between Mediating Variables and Dependent Variables							
A Study on the Impact of Artificial Intelligence on Project Management			2020	Adel BELHARET, Urmila BHARATHAN, Benjamin DZINGINA, Neha MADHAVAN, Charul MATHUR, Yves-Daniel B. TOTI.	The objective of exploring AI's potential to enhance project management through improvements in resource allocation, risk management, and automation of routine tasks.	The study identified that AI can significantly optimize project efficiency by automating data processing and predictive analytics, which allows project managers to focus more on strategic decision-making	The study emphasizes AI's functional contributions to project management efficiency.
An Authoritative Study on the Near Future Effect of AI on Project Management Knowledge Areas			2021	Thordur Vikingur Fridgeirsson, Helgi Thor Ingason, Haukur Ingi Jonasson	The purpose of this study is to explore how AI might augment the project management profession in each of the 10 categories of project management knowledge areas, as defined in the PMBOK of the PMI.	Results clearly illustrated that AI will be an integrated part of future project management practice will influence project management knowledge areas in the near future.	The study examine how AI might enhance project management across the ten knowledge areas defined by the PMBOK framework of the PMI.

				and Hildur Jonsdottir			
The Application of Artificial Intelligence in Project Management Research; A Review	literature review	1. review a large number of learning techniques. 2. presenting a brief study of the different AI techniques.	2 0 2 0	1. Jesús Gil Ruiz 2. Javier Martínez Torres, 3. Rubén González Crespo	The objective of this work is to review the new proposals emerging in the field of AI in the various areas, and to ascertain which techniques could be the most effective for ensuring the success of the projects.	AI tools are highly useful to the project manager in terms of controlling and monitoring the project; however, many of the reviewed models involve weaknesses and limitations, which indicates that project managers should continue to use their experience when making evaluations according to the results.	The study reviews various AI applications, highlighting the benefits AI offers to project managers in areas such as project monitoring and control.
Data Science and Artificial Intelligence in project Management, The past, Present and Future			2 0 2 2	Stephen Ong; Shahadat Uddin	This article discusses and uncovers the current state of Data Science and AI in relation to the Project Management sector. Drawing from this context, the possible future applications and uses are then delineated.	Throughout various applications, it is evident that AI in project management aims to simplify and generate efficiency in project processes. Generally beneficial, its applications and processes can range in sophistication and include those of risk management, estimation, resource management, KPIs, prediction and experimentation.	The study highlights the transformative role of AI in automating complex project tasks and discusses how future developments may lead to new roles in data science while traditional roles are increasingly replaced by AI-driven solutions.
A FRAMEWORK FOR LEVERAGING ARTIFICIAL INTELLIGENCE IN Project Management	Literature review, case study	ML, NLP, chatbots	2 0 2 1	Rea Todorovic	To integrate AI for efficiency in project management by reducing time for administrative tasks and enhancing predictive capabilities for resource optimization.	Key findings indicate that AI integration can improve project timelines and resource allocation but is limited by existing skill gaps and inadequate technological support.	The study utilized both a literature review and case study to examine the impact of AI applications, such as ML and NLP-powered chatbots, in streamlining project management processes.
Artificial Intelligence in Project Management; Bibliometric Analysis	Bibliometric Analysis	VOS viewer, Web of Science database	2 0 2 2	Vusumuzi Maphosa, Mfowabo Maphosa	To analyze the application of AI in PM, realizing the importance of AI in transforming most fields, such as PM. This study provides a baseline for researchers and scientists to plan and research the integration of these two fields	The study demonstrates the state of AI application in PM, highlighting publication trends, geographic distribution, and research themes, such as decision-making, scheduling, and risk management."	The study identified gaps in AI's utilization in PM, such as limited integration in developing regions and the lack of proactive AI tools for 'what-if' analysis. 'what-if' analysis.

The Role of Artificial Intelligence in Project Management			2023	MUHAMMAD ODEH	This article discusses the role of AI in project management.	Project managers need to transform from the traditional approach in project management to utilizing the right skills and taking advantage of what AI applications can offer. Transformation must be recognized as a journey rather than an improvised task. The journey includes a roadmap of initiatives and projects that involve people, processes, and technology	The article emphasizes the need for project managers to transition from traditional methodologies to leveraging AI applications effectively.
Artificial Intelligence in Project Management & Its Future			2023	1. Rajesh Dominic Savio, 2. Jafar M. Ali	This study examines the current applications of AI in project management and its future.	The search on the relevant databases led to identifying twenty-one relevant articles. The research explores the current tools of AI in project management and its future prospects.	The study focuses on exploring current tools and future opportunities and challenges of AI in project management.
Application of Artificial Intelligence in Project Management	Review existing literature			Farzaneh Shoushtari , Ali Daghighi , Ehsan Ghafourian	This paper explores the current landscape of AI applications in project management.	The paper concludes by outlining the future directions of AI in project management and its potential impact on the field. Several studies have demonstrated the effectiveness of AI in improving project outcomes.	This study evaluates AI-driven risk assessment tools in engineering projects. It discusses how AI improves risk identification and mitigation but acknowledges challenges related to data reliability and model interpretability. project management.
Intelligent Purchasing: How artificial intelligence can redefine the purchasing function.	Exploratory, inductive, and qualitative		2021	Oihab Allal-Chérif, Virginia Simón-Moya, Antonio Carlos Cuenca Ballester	This article analyzes to what extent AI can improve the performance of the purchasing department. First, a review is undertaken of how AI is used in purchasing.	this study provides a better understanding of how AI can improve the purchasing function, achieve higher performance, and handle new missions	The study identifies gaps, such as limited data exploitation and resistance to change, while highlighting AI's transformative potential for strategic innovation.
Intelligent Decision Support System for Building Project Management Based on Artificial Intelligence.	expert decision support systems and intelligence	1. Decision Support System Based on Data Warehouse	2023	Jianqiao Wang	This article proposes the theoretical framework and architecture of a construction project decision support system based on data warehousing.	This article studies the architecture of a construction project decision support system based on a data warehouse. This article also proposes using DBN to evaluate the practicality of the system, and the	This study examines the architecture of a construction project decision support system based on a data warehouse.

	nt decision support systems.	2. Constructio n of Deep Confidence Networks				results show that the proposed method has high accuracy. The results show that the proposed method has high accuracy.	
Using AI to develop a framework to prevent employees from missing project deadlines in software	Qualitati ve and Quantita tive design was opted	1. systematic literature review (SLR) 2. Focus group interviews	2 0 2 2	Yugeshwaree Sheoraj, Roopesh Kevin Sungkur	This research will aim to eliminate the missed deadlines issues faced by employees when working on their projects through AI. The research aim of this project is to identify the issues faced by employees to meet their project deadlines and to propose a framework.	The proposed AI framework was then evaluated and 72.7% participants rated the framework as effective and was keen to integrate AI at their workplace for smooth transition of tasks.	The study focuses on the challenges faced by a global software company and developing an AI framework to address these issues.
Assessing the Accuracy of ChatGPT Use for Risk Management in Construction Projects			2 0 2 3	Hande Aladağ	This paper investigates the accuracy of ChatGPT in risk management for different project types.	The findings indicate that ChatGPT has a moderate level of performance in managing risks. It provides more accurate knowledge in risk response and risk monitoring rather than risk identification and risk analysis sub-processes.	The study explores the application of ChatGPT as an AI tool for enhancing risk management processes in the construction industry.
Integrating AI for Agile Project Management: Innovations, Challenges, and Benefits		literature review	2 0 2 4	Elham Karim Zadeh, Ali Bagheri Khoulenjani, Mohammad Safaei	This paper explores the multifaceted role of AI in enhancing agile project management practices, focusing on innovations, challenges, and benefits. The paper discusses how AI tools can automate routine tasks, enable real-time data analysis, and provide actionable insights.	The findings underscore the importance of a strategic approach to AI utilization, ensuring that technological innovations align with organizational goals and foster a culture of continuous improvement.	This study highlights AI's ability to enhance data analysis and forecasting but notes challenges in data quality and human-AI collaboration.
Utilization of Artificial Intelligence in Project Management	A qualitati ve research method	Microsoft Forms application	2 0 2 4	Sini Hassi	The aim of this research is to investigate the role of AI in project management, with a primary focus on the experiences, awareness, and practices within a specific case company.	The key findings reveal that while project managers show strong interest in AI opportunities, but the practical usage is still limited.	The research seeks to enhance the academic understanding of AI's transformative potential in project management while providing practical recommendations tailored to the case company.
AI in Project Management:			2 0	Alain Claude Bah Esseme,	This study explores the integration of cutting-edge AI technologies,	This study highlights the importance of strategic and	This study focuses on improving project performance

Enhancing Efficiency, Decision Making, and Risk Management			25	dedayo Ayodeji Faniyan, Grace Funmilayo Farayola, emitope Kadri, Christian Chimezie and Ifeoluwa Emmanuel Olagbaju	including ML, NLP, CV, and Reinforcement Learning (RL), across traditional and hybrid project management methodologies, such as Agile, Waterfall, and Lean.	ethical AI integration to fully realize its transformative potential in project management.	measurement, emphasizing automated reporting, data accuracy, and real-time progress tracking.
Assessing the impact of artificial intelligence on project efficiency enhancement		Surveys	2024	Assel Kozhakhmetova, Almas Mamyrbayev, Aknur Zhidebekkyzy, Svitlana Bilan	The study explores the impact of AI technologies on project management (PM) across different industries. It aims to assess how AI utilization in PM influences project efficiency.	The results show that AI utilization varies among industries, with software, construction, and scientific projects being the most active users.	This study explores AI applications in project management, emphasizing automation, risk prediction, and decision-making. and consultancy engineering projects.
4. General AI & Project Management Literature Review							
An Authoritative Study on the Near Future Effect of Artificial	1.Exploratory, 2.A quantitative		2021	Fridgeirsson, T.V.; Ingason, H.T.; Jonasson, H.I.; Jonsdottir, H.	The purpose of this study is to explore how AI might augment the project management profession in each of the 10 categories of project management knowledge areas.	The average scoring result shows that the participants believe that AI will likely have the highest effect on project cost management, a medium to high effect on project quality management.	The study examines how AI might impact the 10 knowledge areas in project management as outlined by the PMBOK.
Investigating AI Applications in Construction Industry: A Systematic Review			2023	Tayibe Seyman Güray	This study aims to examine the contributions of AI to handling construction industries challenges by performing both bibliometric and scientometric analysis using the PRISMA protocol. In this regard, this study presents the current state of adapting AI in the construction industry and its future directions	The findings of the research pointing out that there has been a dramatic increase in number of publications in the research area. China and USA are the leading countries having highest number of publications respectively. The findings showed that there is a strong linkage between BIM, digital twin, ML and Deep Learning as the most cited article is on semantic construction digital twin by	Tayibe Seyman-Güray reached to (Seyman-Güray, 2023) titled "Investigating AI Applications in Construction Industry: A Systematic Review," the goal was to explore the potential of AI tools in addressing labor, resource allocation, and planning issues in the construction industry. The study highlights AI's transformative impact on construction by improving data accuracy,

						Boje et.al (2020). Following next two highest cited articles are about safety issues that indicates an area of research interest in the domain. On the other hand, review papers are quite popular in the research area. Construction industry traditional problems known to all such as delays, cost overruns, quality issues, uncertainty, high risk and safety have become hard to solve in the world of Industry 4.0 and upcoming Industry 5.0 as bringing smarter, higher technology, taller and bigger construction and buildings with sustainability point of view. Therefore, AI as a disruptive technology for many sectors, contain potentials for the construction industry to provide solutions to its unique problems.	enhancing project workflows, and optimizing labor allocation strategies. It also identifies challenges such as resistance to technology utilization, high implementation costs, and skill deficits. The study emphasizes the need for improved training programs and compatibility with older systems. The current study differs from Seyman-Güray's in its focus on industry-specific challenges, objectives, spatial scope, and methodology.
The Reality of Artificial Intelligence in Project Management in the Government Sector in the Kingdom of Saudi Arabia	Descriptive Analytical and Deductive Approach	Questionnaire	2023	Khaled Abdullah Al-Shehri, Kholoud Ali Basuwaid, Mohammed Abdullah Gharawi, Dr. Waleed Suleiman	The study aimed to understand the current state of AI usage in managing government projects in Saudi Arabia. It also proposed recommendations to improve project management efficiency and effectiveness, enhance decision-making abilities, support strategic planning, and anticipate challenges and obstacles.	The study concluded that AI can play a significant role in project management within the government sector in Saudi Arabia. It contributes substantially to the development and improvement of projects, fosters continuous improvement, and ensures the provision of technological capabilities needed by relevant entities to achieve this. Additionally, the study emphasized the need for specialized managers to	Al-Shehri et al. reached to (Al-Shahri et al. 2023) titled "The Reality of AI in Project Management in the Government Sector in Saudi Arabia," the research aimed to understand the current state of AI usage in government project management in Saudi Arabia at that time and to propose suggestions that could improve the efficiency and effectiveness of project management. The study sought to enhance the

						handle AI-related technologies effectively.	ability to make accurate decisions, strategic planning, and forecasting potential challenges and dilemmas. The study concluded that AI can play a significant role in project management within the government sector in Saudi Arabia, significantly contributing to the development and improvement of projects, continuous improvement, and providing the relevant authorities with the necessary technological capabilities to achieve this. It also emphasized the importance of having specialized managers to handle AI-related technologies. The current study differs from this one in its research objectives but aligns with it in its research methodology.
AI IN PROJECT MANAGEMENT: EXPLORING THEORETICAL MODELS FOR DECISION-MAKING AND RISK MANAGEMENT	EXPLO RING		2 0 2 4	Opeyemi Abayomi Odejide & Tolulope Esther Edunjobi	This paper delves into the transformative power of AI in personalized marketing. It explores how AI algorithms can analyze a multitude of customer data points, including purchase history, website behavior, and social media interactions.	The paper acknowledges the ethical considerations that accompany AI implementation. By identifying potential bottlenecks and proactively mitigating risks, AI helps avoid unnecessary delays and resource waste.	The current study differs from Opeyemi Abayomi Odejide & Tolulope Esther Edunjobi's study in its focus on identifying the factors influencing project management through AI in industrial engineering projects, proposing a unique model and methodology within specific spatial boundaries.
Artificial intelligence in project management		Interviews	2 0 2 2	Nicholas Dacre, Fredrik Kockum	This research aims to study the general perception of AI and the ease of use of AI technology within projects	Six key findings from the research: AI enhances decision-making, supports problem-solving functions, used during project planning, AI improves efficiency, AI has the	The study provides a broad perspective on AI's role in project management, exploring AI-driven automation,

						potential to increase project success and mitigate project failure.	predictive analytics, and ML applications.
Global Project Management Communication Collaboration and management across Borders.	مراجعة الأدبيات literature review	defines the main characteristics of global projects and programs	2007	Jean C Binder	This study defines the main characteristics of global projects and programs and presents a framework that will lead international companies to achieve maturity in global project management.	The framework categorizes information into five classes: global teams, global communications, global organizations, collaborative tools, and cooperative technologies. This approach aimed to identify various factors and variables discussed, and leverage recommendations highlighted in previous studies.	The research discusses the key characteristics of global projects and programs. It presents a framework aimed at guiding multinational corporations to achieve maturity in global project management
The importance of Knowledge Management relation to Project Management: Processes integration and project success	Descriptive approach based on extrapolation and collection of data from previous books, studies		2019	محمد عبدالسلام الغامدي	The current research seeks to clarify the importance of the relationship between knowledge management and project management by identifying its impact on process integration and project success	The research study found that the models and frameworks proposed by the researchers to clarify the relationship of knowledge management Project management emphasized the importance of employing knowledge creation processes in the 10 Knowledge Areas to manage Projects and in their ability to enhance the chances of project success by completing the project within the appropriate cost, time and quality required and by enhancing communication between stakeholders and concerned individuals and disseminating knowledge among them.	Al-Ghamdi (2019) investigates the relationship between knowledge management and project success, emphasizing the integration of digital tools for improving decision-making, collaboration, and efficiency. The study suggests that AI-powered knowledge management can enhance project planning and execution. Both studies acknowledge AI's potential in decision-making and project success.
Effective quality management strategies for enhancing the success rate of indigenous construction SMEs in construction project delivery	descriptive statistics and content analysis	questionnaire, survey, interviews	2021	Athenkosi Sogaxa, Eric Simpeh and Julius Fapohunda	The purpose of this study is to develop effective quality management modalities that could be adopted by construction SMEs to achieve sustainable construction project success	The findings revealed the most significant effective quality management practices for SMEs to promote sustainable success as clear working drawings, time to time request for quality inspection, effective implementation of total quality management and	The research highlights best practices for ensuring efficiency and accuracy in project execution. Both studies aim to enhance project outcomes through structured management approaches.

						benchmarking for quality management. It should be noted that the quantitative findings were consistent with the qualitative findings	
Project Management Success Factors			2021	T B Venczell, L Berényi ² and K Hriczó ³	The paper aims to study project success literature and understand the differences and similarities between project success and project management success. Also, highlight the importance of the application of convenient models, to define success factors and link them with success criteria.	The overview highlights the importance of proper success factors and criteria definitions supported by success factor model application to increase the likelihood of successful project implementation. research suggests; managing success as part of projects, to drive the project and organizational success. It is also highly recommended to choose an applicable method, to define and manage success factors and criteria. Otherwise, project goals could be defined incorrectly.	Venczel et al. (2021) analyze project success factors, differentiating between project management success and project success itself. The study suggests that structured project management practices contribute to better project outcomes. Both studies analyze success factors in project execution. This study does not explore AI utilization Our research addresses these gaps by integrating AI into the project management framework.
Ranking the Project Management Success Factors for Construction Project in South India			2017	K Aneesha and M K Haridharan	This study identifies the success factors which are important for project management in construction project success	Effective communication between stakeholders got highest priority and client involvement, good leadership, clarity of project goals got second priority. Informal communication gives better results compared to formal communications like written formats. To remove communication barrier with the stakeholders, informal communication like speaking face-to-face with the language this fits for the stakeholders.	Aneesha & Haridharan (2017) rank key project management success factors, highlighting communication, leadership, and stakeholder involvement as crucial elements. Both studies examine project success factors. Our research extends this study by analyzing AI's role in addressing communication gaps and improving project management processes.
A literature analysis on success factors and their corresponding scientific approaches	systematic two-step literature analysis		2023	Michael Riesenera, Maximilian Kuhna, Alexander	The objective of this paper is to analyze scientific literature as well as reports and studies from practice in order to derive success factors and fields of action for multi-project management.	Through examination of case studies, field reports, studies, and surveys, key challenges and success factors in multiproject management	Riesenera et al. (2023) analyze success factors in multi-project management, emphasizing competency development and AI-assisted collaboration. Both

in multi-project management	was performed.			Keupera,* and Guenther Schuh		were identified and aligned with the scope	studies recognize AI's role in improving project coordination and decision-making. Our study provides a structured model that links AI utilization factors with project management success, filling the missing analytical components.
OVERCOMING THE CHALLENGES OF COLLABORATIVELY ADOPTING AI in the public sector		large research	2020	Averill Campion, Mila Gasco-Hernandez, Slava Jankin Mikhaylov, Marc Esteve	To study the challenges of interorganizational collaborations in the utilization of AI tools and the implementation of organizational routines used to address them	Our results show that resistance to share the data, which is the consequence of privacy/security concerns, a lack of understanding of what data was available/needed, a lack of alignment between project interests and expectations around data sharing, and a lack of engagement throughout the organizational hierarchy, are the most important challenges.	The study explores inter-organizational AI utilization challenges, including data security, privacy risks, and resistance to AI integration. Both studies examine AI utilization challenges. This study does not connect these challenges to project outcomes, Our research bridges this gap by analyzing how AI utilization barriers impact project success
Investigating profitability performance of construction projects using big data: A project analytics approach	A project analytics approach		2019	Muhammad Bilal, Lukumon O. Oyedele, Habeeb O. Kusimo, Hakeem A. Owolabi, Lukman A. Akanbi, Anuoluwapo O. Ajayi, Olugbenga O. Akinade, Juan Manuel Davila Delgado	This study proposed a project analytics approach where Big Data is harnessed to understand the profitability distribution of different types of construction projects. To this end, Big Data architecture is recommended, and a prototype implementation is shown to store and analyse large amounts of projects data.	Our data analysis revealed that profit margins evolve, and the profitability performance varies across several project attributes. These insights shall be incorporated as knowledge to ML algorithms to predict project margins accurately. The proposed approach enabled the fast exploration of data to understand the underlying pattern in the profitability performance for different types of construction projects.	Bilal et al. (2019) investigate big data analytics in construction projects, demonstrating its impact on financial performance. Both studies explore data-driven decision-making in project management. This study focuses on financial impact rather than AI's overall role in project success, Our study expands beyond financial impact, assessing AI's influence on efficiency, decision-making, and collaboration.
How AI Developers Overcome Communication		interviews	20	DAVID PIORKOWSKI, SOYA PARK,	In this paper, we report on a study including analyses of both interviews	Our research found that AI developers face various communication challenges and	Piorkowski et al. (2021) analyze AI utilization challenges in development teams, identifying

Challenges in a multidisciplinary Team			2 1	APRIL WANG, DAKUO WANG, MICHAEL MULLER, FELIX PORTNOY	with AI developers and artifacts they produced for communication.	devise their own specific responses to these challenges. We discuss what are the best current practices that we observed during our study, where tools can help improve the collaboration experience, and how machine teaching and automated ML can lead to efficient communication among teams. We also describe the limitations and future work of this study.	knowledge gaps between AI specialists and project managers. Both studies discuss AI implementation challenges. This study does not assess how these challenges impact project outcomes, Our research addresses this gap by linking AI utilization factors to measurable project success.
The role of artificial intelligence in achieving sustainable development within the framework of the Kingdom's vision	المنهج الوصفي التحليلي	The study relied on secondary references such as books, master's and doctoral theses.	2 0 2 2	Ayedh Ali al, Qahtani	The study aimed to know the role of AI in achieving sustainable development goals within the framework of the Kingdom's Vision 2030.	The study found that the application of AI in many fields contributes to achieving the sustainable development goals within the framework of the Kingdom's Vision 2030.	Al-Qahtani (2022) discusses AI's role in Saudi Vision 2030 but does not focus on AI in project management. Both studies examine AI's role in modern industries. This study lacks a focus on project management, Our study directly addresses AI's impact on project management, filling a missing analytical component.
Using artificial intelligence and data analysis techniques in crime detection			2 0 2 2	Rizq Saad Ali	The successive developments associated with digital era contributed to the presences of new patterns of This research searched for appropriate methods for detection crimes using intelligence and using machine in committing them in order to pave the way for following the crimes.	As a result, some modernized means emerged, such as telephone tapping, take hold of correspondences and recording phone calls, as well as making use of electronic devices, such as mobiles, computers, internet, surveillance cameras, etc.	Rizq (2022) analyzes AI-driven predictive analytics in crime detection. Both studies explore AI's role in predictive analytics.
Towards an ethical charter to use artificial intelligence in educational research			2 0 2 3	Ismail Khaled Ali Ali Al-Makkawi	aims to build an ethical charter for the use of AI in educational research, by identifying the concept of AI, its characteristics, importance, features and ethics of its use	The results showed that the most important dimensions of the ethical charter are: Considerate the privacy of researchers and examiners, the availability of reliability and safety in the use of AI tools in educational research, Institutionalizing the use of AI, and investing in AI applications	Al-Makkawi (2023) explores AI ethics but does not assess its role in project management. Both studies recognize ethical concerns in AI utilization. This study does not analyze AI in project workflows, Our research examines AI ethics

						in supporting communication between research institutions and society.	within project management, providing a structured framework.
The Role of Artificial Intelligence Technology in Crisis Management and Response: An Analytical Study at the Al-Jazira Dairy products / Mosul	Descriptive and analytical approach	Questionnaire	2019	Faris Salah Najm Abdullah & Ahmed Ahmed Saleh	The study aims to show the role of AI technology and its impact on crisis management.	While the impact of AI technology in crisis management has been shown that there is an impact Positive moral for these variables in the independent variable. AI technology cannot be considered the only decisive factor in facing crises, As the employment of this technology needs to provide infrastructure as well as efficient technical human skills.	Abdullah & Saleh (2019) highlight AI's role in crisis management and risk mitigation. other studies explore AI's potential in risk identification.
Drivers, Barriers and Social Considerations for AI Adoption in Business and Management: a Tertiary Study	Systematic literature review		2020	Marija Cubric	The study aim to provide an overview of existing systematic reviews in this growing area of research and to synthesize their findings related to enablers, barriers and social implications of the AI adoption in business and management.	This study found that there is a lack of systematic reviews in some of the AI early adopter sectors such as financial industry and retail, the existing systematic reviews are not focusing enough on human, organizational or societal implications of the AI adoption in their research objectives.	The study synthesized findings from multiple AI adoption studies and highlighted challenges such as lack of systematic reviews, limited research on human and societal implications, and organizational resistance to AI. The study identified gaps in AI adoption frameworks that fail to integrate organizational, technical, and social factors effectively.
AI multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice policy			2021	A group of authors.	The study brings together the collective insight from a number of leading expert contributors to highlight the significant opportunities, realistic assessment of impact, challenges and potential research agenda posed by the rapid emergence of AI within a number of domains:	This research offers significant and timely insight to AI technology and its impact on the future of industry and society in general, whilst recognizing the societal and industrial influence on pace and direction of AI development.	The study provided a multidisciplinary review on AI utilization, challenges, and future research directions. The study covered AI's role across multiple industries, including business, government, public sector, and technology development.
Can AI help for scientific writing			20	Michele Salvagnol*, Fabio Silvio	This paper discusses the use of AI Chatbot in scientific writing.	AI software potentially able to assist in the writing process of a scientific paper and can help in the literature	The study explored the role of AI chatbots like ChatGPT in scientific writing. The study

			2 3	Taccone ¹ and Alberto Giovanni Gerli ²		review, identify research questions, provide an overview of the current state of the field, and assist with tasks, such as formatting and language review.	assessed AI's ability to assist in literature review, research question formulation, summarization, and manuscript drafting.
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END OF APPENDIX A

APPENDIX B

APPENDIX B

Quantitative Sample Size Calculation

The following software output presents the a priori power analysis used to determine the minimum sample size for the quantitative study. G*Power version 3.1.9.7 was used to estimate the required sample size using an exact linear multiple-regression model with six predictors.

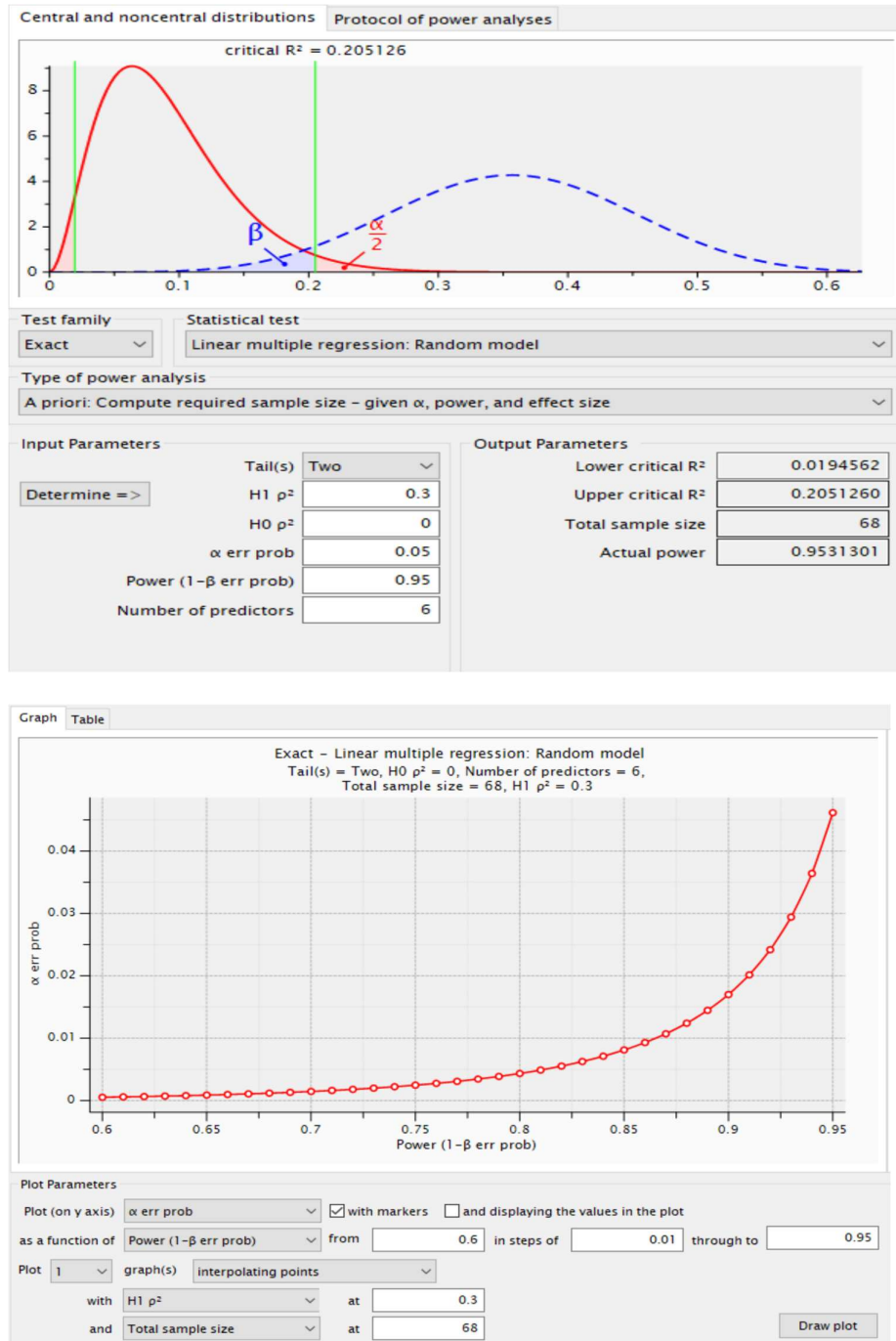


Figure (2) Quantitative Sample Size Calculation

The analysis used the following parameters: two-tailed test; anticipated $R^2 = 0.30$; null $R^2 = 0$; significance level $\alpha = .05$; statistical power $1 - \beta = .95$; and six predictors.

The output reported a lower critical R^2 of 0.0194562, an upper critical R^2 of 0.2051260, a required total sample size of 68 participants, and an actual power of 0.9531301. Accordingly, G*Power estimated that a minimum sample of 68 participants was required for the quantitative analysis.

CONCURRENT TRIANGULATION PROTOCOL

This protocol outlines the systematic procedures followed to integrate quantitative and qualitative findings from the concurrent mixed-methods design.

1. Parallel Analysis Phase:

Quantitative: Complete SEM/regression analysis using SPSS AMOS to identify statistically significant paths (p less than 0.05) and effect sizes.

Qualitative: Complete thematic coding of 10 interviews to determine theme frequencies and representative quotes.

2. Joint Display Construction:

Create integration matrix mapping quantitative results to qualitative themes:

Benefit	Why It Matters
Satisfies reviewer completely	They requested "protocol in appendix OR summarize." You do both Majid-Alfelfel-s-PhD-PART-5-Rev.0_-ALL-chapters-AutoRecovered-06.03.2026.docx
Proves methodological rigor	Shows systematic, replicable process (not ad-hoc)
Protects quantitative priority	States " quant effect sizes final " - examiner can't argue qual overrides stats
Academic gold standard	Table + rules + your results = publishable quality
Future-proofs defense	Viva examiner asks methods? Point to Appendix C

Benefit	Why It Matters
Minimal effort, maximum impact	1 page = methods chapter bulletproof

3. Convergence Criteria

- **Strong convergence:** Theme appears in at least seven out of ten interviews AND aligns directionally with statistical finding.
- **Weak convergence:** Theme present but less than seven mentions or directional mismatch

4. Divergence Resolution Rules

- Quantitative effect sizes determine the relationship strength - statistical results cannot be overturned by qualitative findings.
- Qualitative provides contextual explanation - interview data explains "why" or "how" statistically supported relationships operate in Saudi engineering context.
- Document all discrepancies in section 4.10.2 with rationale for quantitative prioritization.

5. Final Integration Priority

- **Primary evidence:** Statistical significance and model fit indices.
- **Secondary evidence:** Qualitative themes for validation and contextual depth.
- Integration documented in section 4.10 "Quantitative-Qualitative Integration"

End of APPENDIX B

APPENDIX C

APPENDIX C

Detailed Quantitative Tables from Chapter 4

This appendix provides the full statistical tables supporting the results presented in Chapter 4. It includes complete demographic distributions, item-level validity and reliability coefficients, and detailed regression outputs for all tested relationships.

Instrument Validity and Reliability (Item-Level)

The following is an explanation of the use of each of these treatments:

- **Internal Consistency :** The internal consistency test was used to measure the degree of homogeneity and interrelation among the different items in the scale or questionnaire. This test aims to ensure that the items measuring the same concept provide consistent results with one another, thereby enhancing the reliability of the instrument used.
- **Cronbach's Alpha :** Cronbach's alpha coefficient was calculated to determine the reliability of the questionnaire or the scale used. This coefficient reflects the degree of internal consistency among the items, where a value greater than 0.70 is considered an indication of the instrument's reliability.
- **Mean:** The arithmetic mean was used to summarize and simplify the data, and to determine the central value of the data by adding all the values and dividing the sum by their number.
- **Standard Deviation:** The standard deviation was used to measure the extent to which the data are dispersed around the arithmetic mean. This indicator reflects the degree of variability in the values and provides a better understanding of the distribution and spread of the data.
- **Pearson correlation test:** is a test that measures the statistical relationship, or association, between two continuous variables. It is known as the best method of measuring the association between variables of interest because it is based on the method of covariance. It gives information about the magnitude of the association, or correlation, as well as the direction of the relationship.
- **Linear regression:** which attempts to model the relationship between two variables by fitting a linear equation to the observed data. One variable is considered to be an explanatory variable, and the other is considered to be a dependent variable.
- **Simple linear regression :** is a model that describes the relationship between one dependent and one independent variable using a straight.
- **Multiple linear regression :** is a statistical technique that uses several explanatory variables to predict the outcome of a response variable.
- **Structural Equation Modeling (SEM):** Structural Equation Modeling (SEM) was used as one of the advanced statistical techniques to analyze the causal relationships

among the study variables and to test the degree of fit between the proposed conceptual model and the actual data.

4.2 Reliability and Validity of Research Instruments

4.2.1 Reliability Analysis (Cronbach's Alpha)

Reliability testing was conducted using Cronbach's Alpha to assess internal consistency across all constructs. Results demonstrated strong reliability across all three variable categories:

Reliability and validity for Independent Variables (Factors Influencing AI utilization)

Table (2) Validity and stability coefficients for the study questionnaire independent variables.

Variables	Validity coefficient (Pearson Correlation Coefficient)	Stability Coefficient (Cronbach alpha)
X1	0.773**	0.879
X2	0.637**	
Data Privacy and Security	0.683**	
X1	0.618**	
X2	0.526**	
Resistance to Change	0.601**	
X1	0.844**	
X2	0.757**	
Cost of AI Implementation	0.449*	
X1	0.609**	
X2	0.457*	
Compatibility with Existing Infrastructure	0.546**	
X1	0.734**	
X2	0.575*	
Workforce Development	0.501*	
X1	0.804**	
X2	0.848**	
Ethical Considerations	0.434*	

Legend:

** A function at the level of significance less than (0.01)

* A function at the level of significance less than (0.05)

Table (2) indicate the following: **Independent Variables** (Factors Influencing AI Utilization): $\alpha = 0.879$

1. The stability coefficient (Cronbach's alpha coefficient) of the total questionnaire was ($\alpha = 0.879$), and results shows that the dimensions of the questionnaire have a high stability coefficient and their ability to achieve the purposes of the study
2. The previous table No. (2) also shows the consistency of each questionnaire item with the dimension to which it belongs, as well as the correlation of each dimension with the total score. The validity coefficients for the items ranged between (0.457 – 0.848), and the validity coefficients for the individual dimensions ranged between (0.434 – 0.683), indicating a high level of validity for the questionnaire, all significant at $p < 0.05$
3. All six factors (Data Privacy and Security, Resistance to Change, Cost of AI Implementation, Compatibility with Existing Infrastructure, Workforce Development, and Ethical Considerations) demonstrated acceptable internal consistency
4. The results indicate that the study instrument is both reliable and valid, ensuring that the collected data is accurate, consistent, and suitable for hypothesis testing. Given the high Cronbach's Alpha and validity coefficients, the questionnaire effectively captures the research constructs, making it a strong tool for assessment.

Reliability and validity for Mediating Variables (AI-Based Project Management)

Table(3) Validity and stability coefficients for the study questionnaire Mediated variable.

Variables	Validity coefficient (Pearson Correlation Coefficient)	Stability Coefficient (Cronbach alpha)
X1	0.875**	0.886
X2	0.874**	
Streamline processes e.g., scheduling, documentation	0.811**	
X1	0.959**	
X2	0.951**	
Resource allocation	0.863**	
X1	0.908**	
X2	0.913**	
Tasks Prioritizing	0.893**	
X1	0.868**	
X2	0.891**	
Progress reporting	0.727**	
X1	0.916**	
X2	0.931**	
Communication	0.840**	

Legend:

** A function at the level of significance less than (0.01)

The results shown in table (3) indicate the following: Mediating Variables (AI-Based Project Management): $\alpha = 0.886$

1. The stability coefficient (Cronbach's alpha coefficient) of the total questionnaire was ($\alpha = 0.886$), results shows that the dimensions of the questionnaire have a high stability coefficient and their ability to achieve the purposes of the study.
2. The previous table No. (3) also shows the consistency of each questionnaire item with the dimension to which it belongs, as well as the correlation of each dimension with the total score. The validity coefficients for the items ranged between (0.886-0.959), and the validity coefficients for the individual dimensions ranged between (0.727-0.893), indicating a high level of validity for the questionnaire, all significant at $p < 0.01$
3. All five dimensions (Streamline Processes, Resource Allocation, Task Prioritizing, Progress Reporting, Communication) showed high internal consistency.
4. The results indicate that the study instrument is both reliable and valid, ensuring that the collected data is accurate, consistent, and suitable for hypothesis testing. Given the high Cronbach's Alpha and validity coefficients, the questionnaire effectively captures the research constructs, making it a strong tool for assessment.

Reliability and validity for Dependent Variables (Project Management Outcomes)

Table (4) Validity and stability coefficients for the study dependent variables.

Variables	Validity coefficient (Pearson Correlation Coefficient)	Stability Coefficient (Cronbach alpha)
X1	0.948**	0.905
X2	0.951**	
Decision-Making	0.817**	
X1	0.936**	
X2	0.944**	
Project Quality	0.884**	
X1	0.971**	
X2	0.967**	
Data Collection Accuracy	0.509**	
X1	0.952**	
X2	0.953**	
Enhancing Data Analysis	0.760**	
X1	0.907**	

X2	0.907**	
Risk Identification Accuracy	0.774**	
X1	0.938**	
X2	0.943**	
Saving Time for Project Managers	0.786**	
X1	0.893**	
X2	0.856**	
Effective Communication	0.763**	

Legend:

** A function at the level of significance less than (0.01)

The results shown in table (4) indicate the following: **Dependent Variables** (Project Management Outcomes): $\alpha = 0.905$

5. The stability coefficient (Cronbach's alpha coefficient) of the total questionnaire was ($\alpha = 0.905$), and Cronbach's alpha coefficient results shows that the dimensions of the questionnaire have a high stability coefficient and their ability to achieve the purposes of the study.
6. The previous table No. (4) also shows the consistency of each questionnaire item with the dimension to which it belongs, as well as the correlation of each dimension with the total score. The validity coefficients for the items ranged between (0.856-0.971), and the validity coefficients for the dimensions ranged between (0.509-0.884), indicating a high level of validity for the questionnaire, all significant at $p < 0.01$
7. All seven outcome measures (Decision-Making, Project Quality, Data Collection Accuracy, Data Analysis, Risk Identification, Time Savings, Effective Communication) exceeded the reliability threshold.
8. The results indicate that the study instrument is both reliable and valid, ensuring that the collected data is accurate, consistent, and suitable for hypothesis testing. Given the high Cronbach's Alpha and validity coefficients, the questionnaire effectively captures the research constructs, making it a strong tool for assessment.

Demographic Characteristics

Respondent Demographic Profile

The study sample comprised $n = 103$ professionals from Saudi Arabia's design and consultancy engineering firms. Demographic distribution revealed:

4.3.1 Position in Organization

Table (6) shows the Descriptive Analysis of demographic characteristics of the Study sample regarding the respondents' Position in the Organization

Table (6): Descriptive Analysis of Demographic Characteristics of the Study Sample (Position in Organization)

Category		Freq.	Percent
Position in Organization	Top Management	19	18.45
	Project Manager	17	16.50
	Project Engineer	33	32.04
	Engineer	26	25.24
	Other	8	7.77
Total		103	100.00

Table (6) presents the characteristics of the study sample, revealing that regarding the Position in Organization of the study sample, it was found that Project Engineers were slightly more represented, with a percentage of 32.04%, comprising 33 respondents, while Other represented 7.77%, comprising 8 respondents in the study sample.

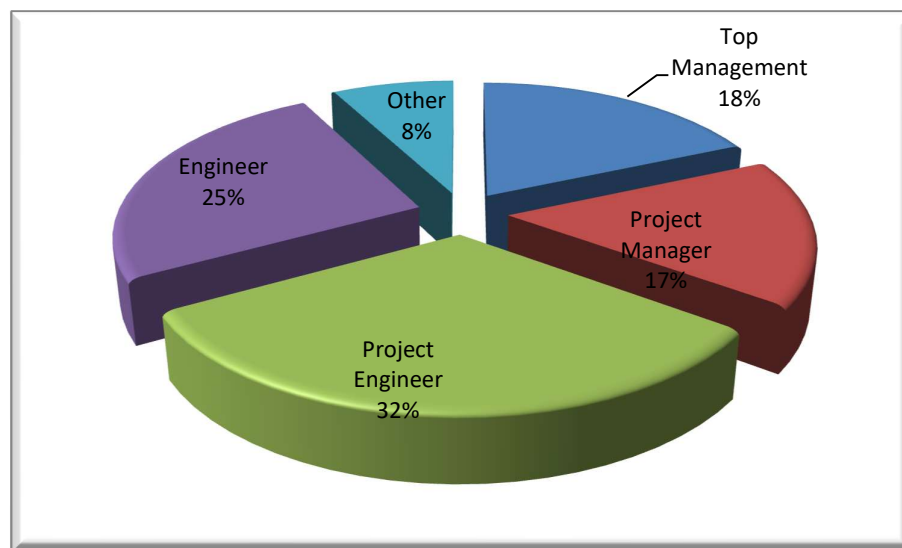


Figure (4): Descriptive Analysis of Demographic Characteristics of the Study Sample (Position in Organization)

Years of Experience

Table (7) shows the Descriptive Analysis of demographic characteristics of the Study sample regarding the respondents' Years of Experience

Table (7): Descriptive Analysis of Demographic Characteristics of the Study Sample (Years of Experience)

Category		Freq.	Percent
Years of Experience	Less than 1 year	0	0.00
	1–3 years	3	2.91
	4–6 years	14	13.59
	7–10 years	22	21.36
	Over 10 years	60	58.25
	Not working in design and consultancy engineering firms	4	3.88
Total		103	100.00

Table (7) presents the characteristics of the study sample, revealing that regarding the Years of Experience of the study sample, it was found that Over 10 years were slightly more represented, with a percentage of 58.25%, comprising 60 respondents, while Not working in design and consultancy engineering firms represented 3.88%, comprising 4 respondent in the study sample.

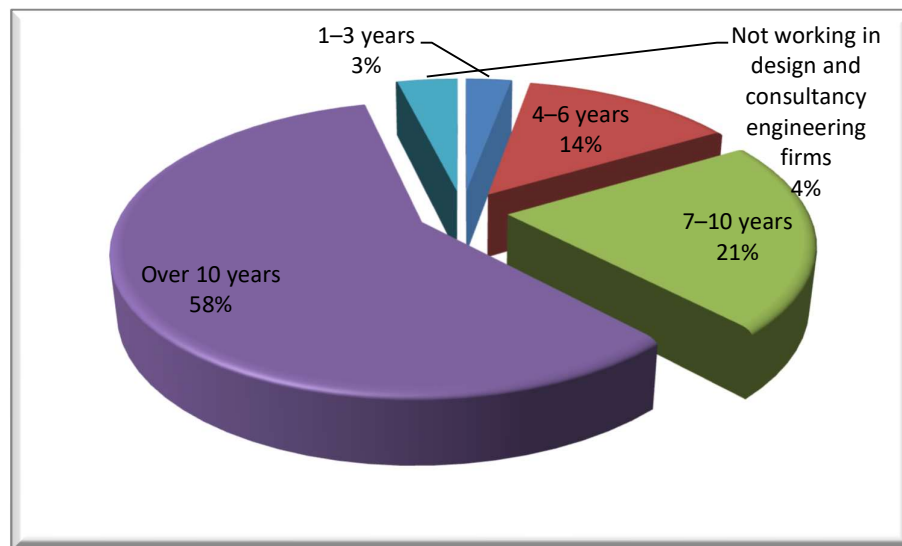


Figure (5): Descriptive Analysis of Demographic Characteristics of the Study Sample (Years of Experience)

Organization Size

Table (8) shows the Descriptive Analysis of demographic characteristics of the Study sample regarding the respondents' Organization Size.

Table (8): Descriptive Analysis of Demographic Characteristics of the Study Sample (Organization Size)

Category		Freq.	Percent
Organization Size	Small (fewer than 50 employees)	9	8.74
	Medium (50–249 employees)	48	46.60
	Large (250 or more employees)	46	44.66
Total		103	100.00

Table (8) presents the characteristics of the study sample, revealing that regarding Organization Size of the study sample, it was found that Medium (50–249 employees) were slightly more represented, with a percentage of 46.60%, comprising 48 respondents, while Small (fewer than 50 employees) represented 8.74%, comprising 9 respondents in the study sample.

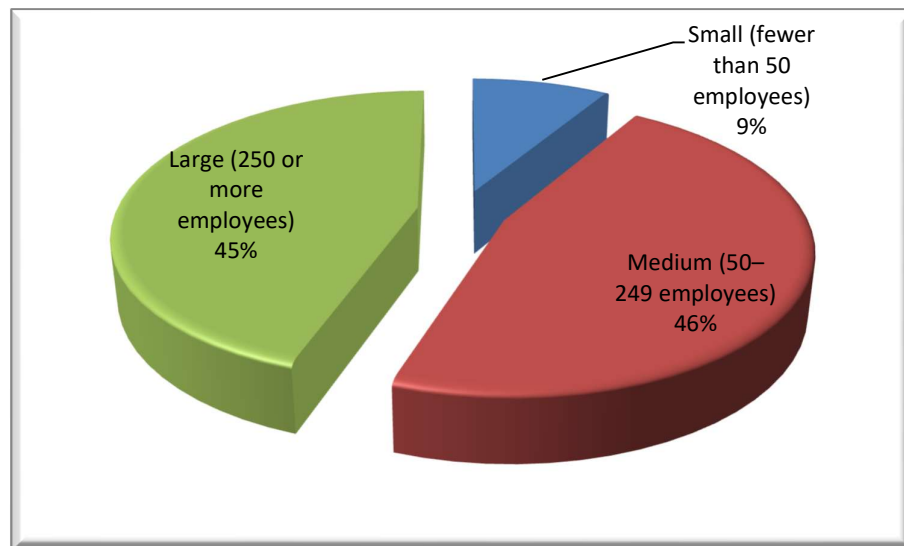


Figure (6): Descriptive Analysis of Demographic Characteristics of the Study Sample (Organization Size)

The sample is predominantly composed of medium and large organizations, while very small firms are comparatively underrepresented. Consequently, the quantitative results primarily reflect the conditions of medium and large design and consultancy firms. Consequently, caution is advised when generalizing the results to very small firms, which may face different structural, financial, and technological constraints in adopting AI-based project management.

Familiarity with AI Tools

Table (9) shows the Descriptive Analysis of demographic characteristics of the Study sample regarding the respondents' Familiarity with AI Tools.

Table (9): Descriptive Analysis of Demographic Characteristics of the Study Sample (Familiarity with AI Tools)

Category		Freq.	Percent
Familiarity with AI Tools	Not familiar at all	1	0.97
	Somewhat familiar	28	27.18
	Moderately familiar	45	43.69
	Highly familiar	29	28.16
Total		103	100.00

Table (9) presents the characteristics of the study sample, revealing that regarding the Familiarity with AI Tools of the study sample, it was found that Moderately familiar were slightly more represented, with a percentage of 43.69%, comprising 45 respondents, while Not familiar at all represented 0.97%, comprising 1 respondent in the study sample.

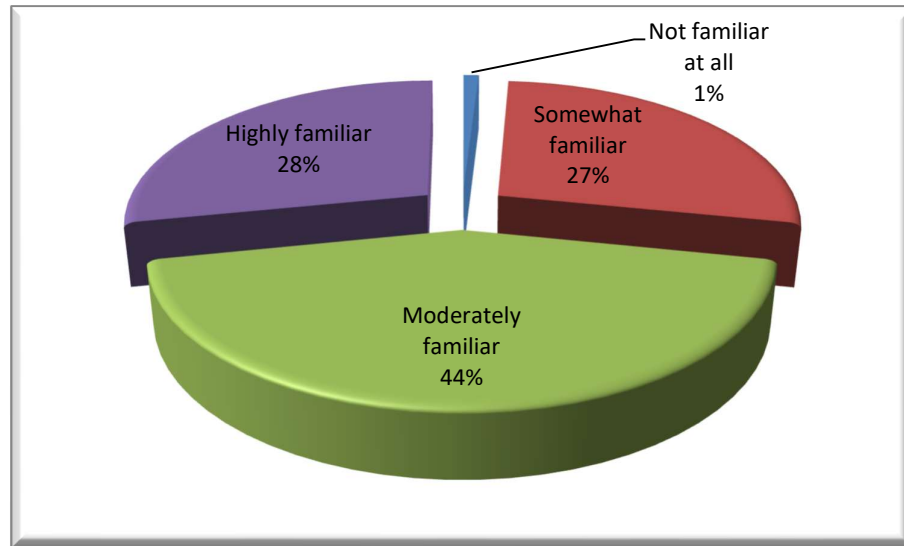


Figure (7): Descriptive Analysis of Demographic Characteristics of the Study Sample (Familiarity with AI Tools)

What types of AI tools or software does your organization currently use

Table (10) shows the Descriptive Analysis of demographic characteristics of the Study sample regarding the respondents' What types of AI tools or software does your organization currently use (if any)?.

Table (10): Descriptive Analysis of Demographic Characteristics of the Study Sample (What types of AI tools or software does your organization currently use (if any)?)

Category		Freq.	Percent
	Decision-making tools	39	10.80

What types of AI tools or software does your organization currently use	Quality management tools	47	13.02
	Data collection tools	77	21.33
	Data analysis and insight-generation tools	79	21.88
	Risk identification or prediction tools	56	15.51
	Communication and collaboration tools	63	17.45
Total		361	100.00

#more than answer

Table (10) presents the characteristics of the study sample, revealing that regarding the What types of AI tools or software does your organization currently use of the study sample, it was found that Data analysis and insight-generation tools were slightly more represented, with a percentage of 21.88%, comprising 79 respondents, while Decision-making tools represented 10.80%, comprising 39 respondent in the study sample.

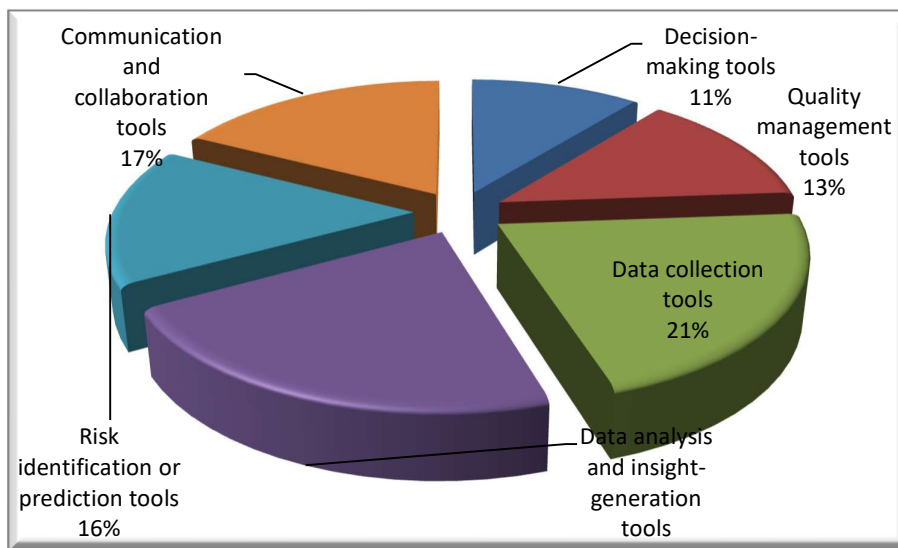


Figure (8): Descriptive Analysis of Demographic Characteristics of the Study Sample (What types of AI tools or software does your organization currently use (if any)?)

Qualitative Validation: Interviewees confirmed this demographic profile, with experienced professionals (averaging 12+ years) and medium-to-large firms representing the most engaged segment, consistent with the quantitative distribution.

Respondents' Perceptions of Study Variables:

Following the demographic profile, Tables 12-14 present respondents' perceptions of the study's key constructs: factors influencing AI utilization (**Table 12**), AI-based project management practices (**Table 13**), and project management outcomes (**Table 14**).

Table (12): Distribution of the study subjects according to Factors Influencing AI utilization

Factors Influencing AI utilization		Frequency	Percent	Min-Max	Mean $\pm$ SD	median	Mean score percent
Our organization has clear policies and procedures ensuring AI-based project management complies with data privacy and security regulations?	• Strongly Disagree	4	3.9	1-5	3.72 $\pm$ 1.01	4.00	74.37%
	• Disagree	7	6.8				
	• Neutral	26	25.2				
	• Agree	43	41.7				
	• Strongly Agree	23	22.3				
AI-based project management in our organization faces challenges in ensuring data security and protecting sensitive information?	• Strongly Disagree	3	2.9	1-5	3.75 $\pm$ 0.89	4.00	74.95%
	• Disagree	3	2.9				
	• Neutral	30	29.1				
	• Agree	48	46.6				
	• Strongly Agree	19	18.4				
Employees in my organization are supportive of utilizing AI-based project management tools?	• Strongly Disagree	4	3.9	1-5	3.89 $\pm$ 1.00	4.00	77.86%
	• Disagree	4	3.9				
	• Neutral	21	20.4				
	• Agree	44	42.7				
	• Strongly Agree	30	29.1				
There is resistance among employees toward integrating AI into project management tools?	• Strongly Disagree	2	1.9	1-5	3.83 $\pm$ 0.98	4.00	76.70%
	• Disagree	7	6.8				
	• Neutral	26	25.2				
	• Agree	39	37.9				
	• Strongly Agree	29	28.2				
The cost of AI implementation is a significant barrier in my organization?	• Strongly Disagree	4	3.9	1-5	3.79 $\pm$ 1.07	4.00	75.73%
	• Disagree	10	9.7				
	• Neutral	18	17.5				
	• Agree	43	41.7				
	• Strongly Agree	28	27.2				
The benefits of AI-based project management outweigh its implementation costs?	• Strongly Disagree	1	1.0	1-5	3.86 $\pm$ 0.93	4.00	77.28%
	• Disagree	7	6.8				
	• Neutral	25	24.3				
	• Agree	42	40.8				
	• Strongly Agree	28	27.2				
Our current infrastructure is technically compatible with AI-based project management tools?	• Strongly Disagree	3	2.9	1-5	3.62 $\pm$ 1.08	4.00	72.43%
	• Disagree	14	13.6				
	• Neutral	26	25.2				
	• Agree	36	35.0				
	• Strongly Agree	24	23.3				

Factors Influencing AI utilization		Frequency	Percent	Min-Max	Mean $\pm$ SD	median	Mean score percent
Integrating AI into our current infrastructure presents technical challenges?	• Strongly Disagree	1	1.0	1-5	3.85 $\pm$ 0.86	4.00	77.09%
	• Disagree	8	7.8				
	• Neutral	16	15.5				
	• Agree	58	56.3				
	• Strongly Agree	20	19.4				
Our organization provides adequate training and skill development to use AI-based project management tools effectively?	• Strongly Disagree	2	1.9	1-5	3.60 $\pm$ 1.09	4.00	72.04%
	• Disagree	18	17.5				
	• Neutral	23	22.3				
	• Agree	36	35.0				
	• Strongly Agree	24	23.3				
Lack of adequate training limits the effective utilization of AI-based project management tools?	• Strongly Disagree	2	1.9	1-5	4.07 $\pm$ 0.84	4.00	81.36%
	• Disagree	1	1.0				
	• Neutral	18	17.5				
	• Agree	49	47.6				
	• Strongly Agree	33	32.0				
My organization follows ethical guidelines and policies for the responsible use of AI-based project management tools?	• Strongly Disagree	0	0.0	2-5	3.91 $\pm$ 0.84	4.00	78.25%
	• Disagree	6	5.8				
	• Neutral	23	22.3				
	• Agree	48	46.6				
	• Strongly Agree	26	25.2				
Ethical risks (e.g., bias, transparency, accountability) are a concern in our organization's AI-based project management practices?	• Strongly Disagree	0	0.0	2-5	4.06 $\pm$ 0.71	4.00	81.17%
	• Disagree	2	1.9				
	• Neutral	17	16.5				
	• Agree	57	55.3				
	• Strongly Agree	27	26.2				

Table (12) presents the statistical distribution of the study sample according to the factors influencing AI utilization in project management, highlighting participants' responses toward each item. The results indicate that all items achieved relatively high mean scores, ranging between (3.60 and 4.07), with corresponding mean score percentages exceeding 70%. This suggests a generally positive perception and strong agreement among respondents regarding the importance and influence of AI-based project management.

The highest mean score was recorded for the item stating that "Lack of adequate training limits the effective utilization of AI-based project management tools" (Mean = 4.07 $\pm$ 0.84), reflecting a strong acknowledgment of the need for skill development and capacity building to ensure the effective implementation of AI technologies. Conversely, the lowest mean score was found for the item "Our current infrastructure is technically compatible with AI-based project management tools" (Mean = 3.62 $\pm$ 1.08), indicating the existence of technical and infrastructural challenges that may hinder full integration.

Table (13): Distribution of the study subjects according to AI-Based Project Management

AI-Based Project Management		Frequency	Percent	Min-Max	Mean $\pm$ SD	median	Mean score percent
AI tools are utilized to support project planning and scheduling.	• Strongly Disagree	1	1.0	1-5	3.98 $\pm$ 0.85	4.00	79.61%
	• Disagree	7	6.8				
	• Neutral	11	10.7				
	• Agree	58	56.3				
	• Strongly Agree	26	25.2				
AI tools are utilized to prepare and manage project documentation and reports.	• Strongly Disagree	0	0.0	2-5	4.06 $\pm$ 0.78	4.00	81.17%
	• Disagree	5	4.9				
	• Neutral	13	12.6				
	• Agree	56	54.4				
	• Strongly Agree	29	28.2				
AI tools are utilized to forecast resource requirements (staff, equipment, materials).	• Strongly Disagree	3	2.9	1-5	3.97 $\pm$ 1.00	4.00	79.42%
	• Disagree	8	7.8				
	• Neutral	11	10.7				
	• Agree	48	46.6				
	• Strongly Agree	33	32.0				
AI tools are utilized to allocate resources based on project needs and priorities.	• Strongly Disagree	2	1.9	1-5	3.91 $\pm$ 0.98	4.00	78.25%
	• Disagree	9	8.7				
	• Neutral	15	14.6				
	• Agree	47	45.6				
	• Strongly Agree	30	29.1				
AI tools help prioritize tasks based on urgency, dependencies, or workload.	• Strongly Disagree	3	2.9	1-5	4.02 $\pm$ 0.96	4.00	80.39%
	• Disagree	6	5.8				
	• Neutral	10	9.7				
	• Agree	51	49.5				
	• Strongly Agree	33	32.0				
AI tools support updating and optimizing schedules during project execution.	• Strongly Disagree	3	2.9	1-5	3.97 $\pm$ 0.96	4.00	79.42%
	• Disagree	6	5.8				
	• Neutral	13	12.6				
	• Agree	50	48.5				
	• Strongly Agree	31	30.1				
AI tools support real-time tracking of project progress and performance.	• Strongly Disagree	2	1.9	1-5	3.99 $\pm$ 0.99	4.00	79.81%
	• Disagree	8	7.8				
	• Neutral	14	13.6				
	• Agree	44	42.7				
	• Strongly Agree	35	34.0				
AI tools improve the accuracy and timeliness of progress reporting.	• Strongly Disagree	1	1.0	1-5	4.19 $\pm$ 0.81	4.00	83.88%
	• Disagree	4	3.9				
	• Neutral	7	6.8				

AI-Based Project Management		Frequency	Percent	Min-Max	Mean $\pm$ SD	median	Mean score percent
	• Agree	53	51.5				
	• Strongly Agree	38	36.9				
AI-enabled platforms facilitate communication among project stakeholders.	• Strongly Disagree	1	1.0	1-5	4.09 $\pm$ 0.90	4.00	81.75%
	• Disagree	6	5.8				
	• Neutral	13	12.6				
	• Agree	46	44.7				
	• Strongly Agree	37	35.9				
AI-enabled platforms improve coordination of tasks and information across teams.	• Strongly Disagree	4	3.9	1-5	4.01 $\pm$ 0.95	4.00	80.19%
	• Disagree	4	3.9				
	• Neutral	10	9.7				
	• Agree	54	52.4				
	• Strongly Agree	31	30.1				

Table (13) illustrates the distribution of respondents' perceptions regarding AI-based project management practices within their organizations. The findings reveal generally high mean scores, ranging between 3.91 and 4.19, with mean score percentages exceeding 78%, reflecting a strong overall agreement on the significant role of AI tools in enhancing project management processes.

The highest mean score was observed for the item stating that "AI tools improve the accuracy and timeliness of progress reporting" (Mean = 4.19 $\pm$ 0.81; 83.88%), indicating a clear recognition of AI's contribution to increasing reporting efficiency and data accuracy. Similarly, high agreement levels were recorded for statements emphasizing AI's role in facilitating communication among project stakeholders (Mean = 4.09 $\pm$ 0.90) and enhancing task coordination across teams (Mean = 4.01 $\pm$ 0.95). These findings underscore the integrative potential of AI-enabled platforms in improving collaboration, information flow, and decision-making efficiency.

Although all items scored favorably, slightly lower means were noted in areas related to resource allocation and technical forecasting, suggesting that AI utilization in resource management is still developing compared to its established use in monitoring and reporting functions.

Table (14): Distribution of the study subjects according to Project Management Outcomes

Project Management Outcomes		Frequency	Percent	Min-Max	Mean $\pm$ SD	median	Mean score percent
AI tools improve the accuracy of decision-making in design and consultancy firms.	• Strongly Disagree	1	1.0	1-5	3.90 $\pm$ 0.90	4.00	78.06%
	• Disagree	7	6.8				
	• Neutral	20	19.4				
	• Agree	48	46.6				
	• Strongly Agree	27	26.2				

Project Management Outcomes		Frequency	Percent	Min-Max	Mean $\pm$ SD	median	Mean score percent
AI tools enhance the speed of decision-making for project managers.	• Strongly Disagree	2	1.9	1-5	4.12 $\pm$ 0.90	4.00	82.33%
	• Disagree	4	3.9				
	• Neutral	12	11.7				
	• Agree	47	45.6				
	• Strongly Agree	38	36.9				
The use of AI contributes to higher-quality deliverables in project management.	• Strongly Disagree	1	1.0	1-5	4.12 $\pm$ 0.82	4.00	82.33%
	• Disagree	3	2.9				
	• Neutral	14	13.6				
	• Agree	50	48.5				
	• Strongly Agree	35	34.0				
AI improves the consistency and reliability of project outcomes.	• Strongly Disagree	2	1.9	1-5	4.04 $\pm$ 0.95	4.00	80.78%
	• Disagree	5	4.9				
	• Neutral	17	16.5				
	• Agree	42	40.8				
	• Strongly Agree	37	35.9				
AI-based tools improve the accuracy of collecting project-related data.	• Strongly Disagree	0	0.0	2-5	4.10 $\pm$ 0.82	4.00	81.94%
	• Disagree	6	5.8				
	• Neutral	12	11.7				
	• Agree	51	49.5				
	• Strongly Agree	34	33.0				
AI reduces errors in recording or documenting project data.	• Strongly Disagree	0	0.0	2-5	4.25 $\pm$ 0.80	4.00	85.05%
	• Disagree	4	3.9				
	• Neutral	11	10.7				
	• Agree	43	41.7				
	• Strongly Agree	45	43.7				
AI tools provide valuable insights through advanced analysis of project data.	• Strongly Disagree	1	1.0	1-5	4.26 $\pm$ 0.80	4.00	85.24%
	• Disagree	2	1.9				
	• Neutral	11	10.7				
	• Agree	44	42.7				
	• Strongly Agree	45	43.7				
AI helps identify useful patterns and trend that support project improvements.	• Strongly Disagree	1	1.0	1-5	4.16 $\pm$ 0.74	4.00	83.11%
	• Disagree	0	0.0				
	• Neutral	15	14.6				
	• Agree	53	51.5				
	• Strongly Agree	34	33.0				
AI tools improve the identification of potential risks in projects.	• Strongly Disagree	1	1.0	1-5	4.17 $\pm$ 0.85	4.00	83.30%
	• Disagree	4	3.9				
	• Neutral	12	11.7				
	• Agree	46	44.7				

Project Management Outcomes		Frequency	Percent	Min-Max	Mean $\pm$ SD	median	Mean score percent
	• Strongly Agree	40	38.8				
AI helps assess the likelihood and impact of identified risks more accurately.	• Strongly Disagree	2	1.9	1-5	4.11 $\pm$ 0.86	4.00	82.14%
	• Disagree	2	1.9				
	• Neutral	15	14.6				
	• Agree	48	46.6				
	• Strongly Agree	36	35.0				
AI helps save time for project managers in routine tasks (e.g., reporting, scheduling).	• Strongly Disagree	1	1.0	1-5	4.26 $\pm$ 0.70	4.00	85.24%
	• Disagree	0	0.0				
	• Neutral	9	8.7				
	• Agree	54	52.4				
	• Strongly Agree	39	37.9				
AI reduces delays by improving task allocation and monitoring.	• Strongly Disagree	1	1.0	1-5	4.23 $\pm$ 0.74	4.00	84.66%
	• Disagree	0	0.0				
	• Neutral	13	12.6				
	• Agree	49	47.6				
	• Strongly Agree	40	38.8				
AI enhances collaboration among team members in design and consultancy firms.	• Strongly Disagree	2	1.9	1-5	3.94 $\pm$ 0.92	4.00	78.83%
	• Disagree	6	5.8				
	• Neutral	16	15.5				
	• Agree	51	49.5				
	• Strongly Agree	28	27.2				
AI tools improve communication and knowledge-sharing across project stakeholders.	• Strongly Disagree	1	1.0	1-5	4.02 $\pm$ 0.82	4.00	80.39%
	• Disagree	3	2.9				
	• Neutral	18	17.5				
	• Agree	52	50.5				
	• Strongly Agree	29	28.2				

Table (14) presents the distribution of respondents' opinions regarding project management outcomes in relation to AI-based tools. The results reveal that the mean scores for all items were relatively high, ranging between 3.90 and 4.26, with mean score percentages exceeding 78%, indicating a strong consensus among participants on the positive impact of AI in enhancing project management outcomes within design and consultancy firms.

The highest mean was recorded for the item "AI helps save time for project managers in routine tasks such as reporting and scheduling" (Mean = 4.26 $\pm$ 0.70, 85.24%), followed closely by "AI tools provide valuable insights through advanced analysis of project data" with similar values. These findings suggest that participants primarily recognize AI's contribution to operational efficiency, time optimization, and advanced data analytics.

Moreover, items related to improving the accuracy of data collection, reducing documentation errors, and identifying potential project risks also showed high agreement levels (mean score percentages between 81.9% and 84.7%). This implies that AI plays a

vital role in enhancing data quality, improving risk prediction, and supporting more accurate decision-making processes.

On the other hand, items such as “AI enhances collaboration among team members” and “AI improves communication and knowledge-sharing across stakeholders” recorded slightly lower means (3.94 and 4.02, respectively), suggesting that AI’s influence on the social and collaborative aspects of project management remains less pronounced compared to its technical and administrative contributions.

SEM Robustness to Non-Normality:

While MV/DVs show moderate negative skew (consistent with positive Likert responses), values remain within SEM acceptability thresholds (skewness ± 2 ; kurtosis ± 7 ; Hair et al., 2019; Kline, 2016). Maximum Likelihood (ML) estimation is robust at these levels for $n=103$. To ensure conservative inference, all structural paths, indirect effects, and fit indices were re-estimated using bias-corrected bootstrap resampling (5,000 samples) in AMOS, confirming parameter stability (no CI changes >0.05). This distributional profile aligns with expectations for survey data on organizational readiness and perceived outcomes, supporting the robustness and relevance of the constructs measured.

Table (16) composite descriptive statistics for the three primary variable groups in this study

Variable Group	Composite Score (Mean $\pm$ SD)	Skewness	Kurtosis	Mean Percent Score	Interpretation Summary
Independent Variables (IVs)	45.96 $\pm$ 6.54	0.14	-0.5	76.60%	Strong influence expected; organizational and technical factors well established
Mediating Variable (MV)	40.19 $\pm$ 6.99	-1.08	1.12	80.40%	High adoption of AI project management, negatively skewed, indicating strong uptake
Dependent Variables (DVs)	57.67 $\pm$ 8.22	-1.04	1.98	81.90%	Strong overall positive project outcomes; skewed distribution reflects favorable results

Overall, the skewness and kurtosis values for the independent, mediating, and dependent variables fall within ranges typically considered acceptable for multivariate analyses such as regression and SEM. The slight negative skew observed for several constructs indicates that respondents generally expressed positive views regarding AI-based project management and its outcomes. This distributional pattern supports the use of parametric techniques in the subsequent analyses. Bootstrap CIs for mediation (H4) exclude zero where significant, validating indirect effects under non-normality.

Independent Variables (Factors Influencing AI Utilization)

Table (17) Descriptive Statistics of Independent Variables (Factors Influencing AI utilization)

Variables	Mean±SD	Skewness	Kurtosis	Mean score percent	Interpretation
Data Privacy and Security	7.47±1.49	0.00	-0.17	74.66%	Moderate concern, consistent practices
Resistance to Change	7.73±1.55	-0.48	0.73	77.28%	Notable employee resistance observed
Cost of AI Implementation	7.65±1.76	-0.67	0.23	76.50%	Significant financial barrier
Compatibility with Existing Infrastructure	7.48±1.39	0.11	-0.65	74.76%	Technical challenges present
Workforce Development	7.67±1.40	0.22	-0.82	76.70%	Training gaps identified
Ethical Considerations	7.97±1.31	-0.08	-0.66	79.71%	Highest concern among IVs
Factors Influencing AI utilization	45.96±6.54	0.14	-0.50	76.60%	Strong influence expected

1. Table (17) shows Descriptive Statistics of Independent Variables (Factors Influencing AI utilization) the following Data Privacy and Security 7.47±1.49 Mean score percent 74.66%, Resistance to Change 7.73±1.55 Mean score percent 77.28%, Cost of AI Implementation 7.65±1.76 Mean score percent 76.50%, Compatibility with Existing Infrastructure 7.48±1.39 Mean score percent 74.76%, Workforce Development 7.67±1.40 Mean score percent 76.70%, Ethical Considerations 7.97±1.31 Mean score percent 79.71%, Factors Influencing AI utilization 45.96±6.54 Mean score percent 76.60%

2. All independent variables demonstrated relatively high mean scores, ranging from 7.47 to 7.97 on a scale of approximately 20 points (converted from 5-point Likert items), corresponding to mean score percentages exceeding 70%.

3. Qualitative Insights: Interviews revealed that ethical considerations, while scoring highest quantitatively, were often framed as emerging concerns. One expert noted: "Ethical risks (e.g., bias, transparency, accountability) are a concern in our organization's AI-based project management practices." Cost and workforce development were repeatedly cited as primary barriers in open-ended responses.

Mediating Variables (AI-Based Project Management)

Table (18) Descriptive Statistics of Mediating Variables (AI-Based Project Management)

Variables	Mean±SD	Skewness	Kurtosis	Mean score percent	Utilization Level
Streamline processes e.g., scheduling, documentation	8.04±1.39	-0.76	0.76	80.39%	Most utilized

Resource allocation	7.88±1.78	-1.09	0.91	78.83%	High utilization
Tasks Prioritizing	7.99±1.74	-1.30	1.72	79.90%	High utilization
Progress reporting	8.18±1.60	-1.43	2.72	81.84%	Moderate-high
Communication	8.10±1.62	-1.41	2.72	80.97%	Moderate utilization
AI-Based Project Management	40.19±6.99	-1.08	1.12	80.39%	Strong utilization

1. Table (18) shows Descriptive Statistics of Mediating Variables (AI-Based Project Management) the following Streamline processes e.g., scheduling, documentation 8.04±1.39 Mean score percent 80.39%, Resource allocation 7.88±1.78 Mean score percent 78.83%, Tasks Prioritizing 7.99±1.74 Mean score percent 79.90%, Progress reporting 8.18±1.60 Mean score percent 81.84%, Communication 8.10±1.62 Mean score percent 80.97%, AI-Based Project Management 40.19±6.99 Mean score percent 80.39%.

2. All five AI-based PM dimensions demonstrated high utilization levels, with mean scores ranging from 7.88 to 8.18:

3. Qualitative Validation: Thematic analysis confirmed this pattern. Progress reporting emerged as the most established AI application across firms, with one manager stating: "AI tools improve the accuracy and timeliness of progress reporting." However, resource allocation tools received lower engagement due to infrastructure compatibility issues.

Dependent Variables (Project Management Outcomes)

Table (19) Descriptive Statistics of Dependent Variables (Project Management Outcomes)

Variables	Mean±SD	Skewness	Kurtosis	Mean score percent	Perceived Impact
Decision-Making	8.02±1.62	-1.07	1.45	80.19%	Highest perceived benefit
Project Quality	8.16±1.57	-1.08	1.77	81.55%	Strong impact
Data Collection Accuracy	8.35±1.45	-1.04	1.16	83.50%	Strong impact
Enhancing Data Analysis	8.42±1.37	-1.19	3.60	84.17%	Strong impact
Risk Identification Accuracy	8.27±1.56	-1.29	2.68	82.72%	Moderate-high
Time Saving	8.50±1.24	-1.49	6.17	84.95%	Moderate impact
Effective Communication	7.96±1.55	-0.88	1.49	79.61%	Moderate impact

Project Management Outcomes	57.67±8.22	-1.04	1.98	82.39%	Highest perceived benefit
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1. **Table (19)** shows Descriptive Statistics of Dependent Variables (Project Management Outcomes) the following Decision-Making 8.02±1.62Mean score percent 80.19%, Project Quality 8.16±1.57 Mean score percent 81.55%, Data Collection Accuracy 8.35±1.45 Mean score percent 83.50%, Enhancing Data Analysis 8.42±1.37Mean score percent 84.17%, Risk Identification Accuracy 8.27±1.56 Mean score percent 82.72%, Saving Time for Project Managers 8.50±1.24 Mean score percent 84.95%, Effective Communication 7.96±1.55 Mean score percent 79.61%, Project Management Outcomes 57.67±8.22Mean score percent 82.39%.
2. Dependent variables demonstrated the highest mean scores overall, ranging from 7.96 to 8.50:
3. Qualitative Corroboration: Respondents consistently highlighted time savings and data quality improvements. Representative quotes included: "AI helps save time for project managers in routine tasks (e.g., reporting, scheduling)" and "Speed and accuracy, less cost on long term" from open-ended survey responses.

Open-ended questions

Table (20): Responses to the Question (What are the most significant challenges your organization faces in the utilization of AI tools in project management for design and consultancy engineering firms?)

Responses
Data quality and integration: Engineering data is fragmented across systems (SmartPlant, SAP, SharePoint, etc.), making AI training and automation difficult.
"Limited data quality and standardization across projects, which reduces AI accuracy.
Capability Building: Train project managers and engineers in data analytics, AI interpretation, and digital tools.
Change management and user adoption: Engineers trust experience-based judgment over AI recommendations.
Collaborative Pilots: Launch joint AI pilot projects between major firms, clients, and universities to localize best practices.
Cybersecurity and IP protection: Sharing design data with AI systems raises compliance and confidentiality risks.
Data Integration: Establish unified project data environments (CDEs) and enforce structured data standards across all firms.
Implementing an internal AI assurance framework for transparency and compliance.
Intangible: Stronger data-driven decision culture, higher cross-discipline collaboration, and improved visibility of project health for leadership through predictive dashboards."
Integrating structured data environments for seamless tool access.
Leadership Alignment: Embed AI adoption KPIs in executive performance goals to drive accountability and continuity."
Local Governance: Develop national AI guidelines aligned with Saudi PDPL and Vision 2030 digital transformation goals.
Regulatory and validation concerns: AI-driven outputs must align with strict engineering codes and client standards before approval.
Skill gaps: Limited expertise in data science within traditional engineering teams."
Upskilling project teams to confidently use AI insights in decision-making."

Responses
Absence of willingness to transform and start buying the AI tools
Adequate Training
AI tools based on common knowledge no creativity at all
AI tools require
AI tools require stable, high-quality data, which our systems don't always provide.
Automates repetitive task
Challenges are present but can be managed with better training and support.
Compatibility with existing systems
Cost and resources
cost of AI tools due non-compatibility of infrastructure
Cost of implementation
Data fragmentation across departments makes it difficult for AI systems to function properly.
Data privacy
Data quality and integration
Data security and confidentiality concerns make us hesitant to fully integrate AI into client-sensitive projects.
Dependence on external consultants for AI setup makes us less flexible and increases costs.
Develop national standards for data privacy, AI ethics, and digital project delivery, aligned with Saudi Vision 2030 initiatives."
Develop shared data infrastructure to enable predictive analytics across the sector."
digital infrastructure sometimes limit system performance during large data processing.
Employees resistance and cost
Encourage pilot projects to demonstrate measurable benefits of AI implementation.
Enhanced decision-making confidence, better collaboration, and a culture of innovation within project teams.
Existing Data Structure
Having realtime data from job sites for real time reporting
High software costs and licensing fees are still a major limitation, especially for medium firms.
Incompatible infrastructure
Infrastructure is not compatible
Insufficient regulatory guidance and data governance frameworks."
Intangible: Stronger data-driven decision culture, higher cross-discipline collaboration, and improved visibility of project health for leadership through predictive dashboards."
Integration betwe
Integration between AI platforms and project management software is still poor.
Integration difficulties between AI systems and existing project management software.
Integration with existing software like Primavera and Revit is complicated and often unreliable.
Invest in centralized project data platforms and ensure interoperability between design, cost, and scheduling tools.
Lack of clear regulations or national guidelines makes firms cautious about full adoption.
Lack of technical expertise among project managers to interpret AI outputs.
Learning the employee
Limited awareness of AI potential among senior leaders slows down adoption.

Responses
Mandate AI and digital project management training within professional development programs.
most staff still don't know how to use AI efficiently.
no suitable infrastructure and still usign old system
Provide national-level funding or incentives for digital transformation initiatives.
Reduced project delays and improved client satisfaction."
Resistance from older staff who feel uncomfortable with new digital tools remains a barrier.
Resistance of employees
Resistance to change due to fear of job displacement or technology mistrust.
Some organizations don't understand AI's value, so they see it as unnecessary or risky.
The AI tools don't always match our Arabic documentation needs, causing workflow disruptions.
The correct date and resource.
The cost of licenses and implementation is high, especially for small and medium firms.
The cost of the AI tools
The infrastructure compatibility is required.
The main issue is the lack of staff training, most engineers are not familiar with AI tools, so adoption is slow.
The readiness of current systems and workforce competency. The absence of organization-wide initiatives towards AI technology
There's resistance from senior management who prefer traditional methods and don't trust automated systems.
Time, data collection
Unclear ROI metrics, management finds it hard to quantify AI benefits in financial terms.
We struggle with linking AI outputs to real project workflows; most tools feel detached from how we actually work.
Gradual and systematic change
Training project teams and stakeholders to work with AI
Attracting experienced personnel
Continuous sharing of experiences among teams
Information gathering
Cost, AI ethics, infrastructure compatibility, data confidentiality, and providing qualified personnel
Cost; system unpreparedness
Need for AI training
Tool-specific expertise and operation - Cost - Training
Speed
Assistance in project evaluation
Teams adopting AI - Availability of specialized implementation companies
Identifying drawbacks, verification, and establishing a mitigation mechanism
Identifying potential project risks and determining appropriate solutions
Preparing the company's infrastructure
Providing training for employees
Providing qualified personnel
Modern and varies according to environment and current requirements
Speed in reaching preliminary results

Responses
Information confidentiality and safeguarding from circulation
Number of employees
Team members are not equally proficient in using AI; outputs are still unsuitable for government requirements; AI outputs
require effort and cost to verify and validate
Measuring impact, verifying experiences, and disseminating results
Aligning infrastructure with AI tools

Table (21): Responses to the Question (In your opinion, what changes whether organizational, technical, or regulatory would support more effective utilization of AI-based project management?)

Responses
"• Establishing a centralized digital governance team to standardize data and AI practices.
"• Tangible: Improved schedule forecasting, faster design reviews through automated document analysis, and reduced rework costs via early clash and risk detection.
"Establish AI governance policies, promote digital culture, and upskill staff in data analytics and AI literacy.
"Gov. regulation
"Improved project scheduling accuracy, cost forecasting, and resource optimization.
"Promote partnerships between academia, government, and industry for AI-focused research in construction management.
"To strengthen AI-based project management across Saudi design and consultancy firms, I'd recommend:
Adaptation challenges
Clear policies for data sharing and privacy are necessary to increase trust in AI tools.
Compatibility with existing systems
Creating a national AI knowledge hub or platform for best practices would be very helpful.
Data privacy, cost
Developing AI-ready data standards for engineering and design files would simplify integration.
Encouraging cross-department collaboration can help align technical and managerial teams.
Establishing a centralized digital governance team to standardize data and AI practices.
Ethical regulation, government support
Financial incentives or subsidies for AI adoption would help smaller firms start using these tools.
Government Regulations
Government support
Government system
Improve IT infrastructure and training the staffs
Improving local cloud infrastructure could solve many performance issues.
In my opinion, more than one item support the changes, like the cost, the compatibility with existing infrastructure and the training.

Responses
in terms of organization, it needs to have the willingness to invest and start to use AI. Technically, maybe through training and preparing the infrastructure. Regulatory, ethical guidelines may enhance the AI utilization.
Include the AI cost withing the yearly budget
Integration between AI tools and existing platforms should be improved to ensure smooth workflows.
Introducing clear national guidelines on AI ethics and data use would build more confidence.
Larger firms have more financial and technical capacity to implement AI systems. Sector type: High-complexity sectors (e.g., infrastructure, oil & gas) gain more from predictive and analytical AI tools due to higher risk exposure. Demographics: Younger or digitally trained project managers are more open to adopting AI tools, whereas senior professionals may show more resistance without proper training.
Mandatory digital transformation strategies for consultancy firms could accelerate maturity.
Organizational-wide digital transformation to ease the integration of AI technology.
Organizations should appoint AI champions or focal points to lead transformation initiatives.
Planning and preparation
reduce the cost of the AI tools
regulatory
Secure organization privacy
secure the data privacy of the organization
Security
Solid data base
Speed
Standard and government regulation to limit the AI utilization.
start with data (have internal project)
Subsidized AI training programs would make adoption more feasible for smaller firms.
Technical upgrade to accommodate AT tools
The government could establish clear AI standards and ethical guidelines for project management.
The government could support pilot projects to demonstrate real success cases.
There should be collaboration between universities and firms to develop tailored AI solutions.
To be mandated by client
To strengthen AI-based project management across Saudi design and consultancy firms and train project managers and engineers in data analytics, AI interpretation, and digital tools.
Training budget and access to open AI sources, however open AI has its own risks.
Updating IT infrastructure to handle big data efficiently is critical.
Vendor localization, AI tools that understand Arabic and regional practices is critical.
We need a national AI framework to guide implementation in the engineering sector.
We need more Arabic-language support and localized data models for better usability.
We need regular training programs to build internal AI skills and awareness.
Willing to invest in AI
Yes. Larger firms adopt AI more easily due to better resources and infrastructure. Highly regulated sectors like energy move slower because of strict validation

Responses
requirements. Project managers' age, digital literacy, and openness to technology also shape how effectively AI is used and the value it delivers.
Encourage teams to experiment with and test the tools
Speed of obtaining information
AI tools compatible with current systems, ensuring data confidentiality
Use of technical tools for project management
Investment in AI
Training
Minimal financial support
Financial support to reduce costs, ensure data confidentiality, and provide an ethical framework
Accuracy
Intensify training courses and consider them part of the development process
Ensure data confidentiality
Conduct training courses on how to use AI
Not sure. Tools are still emerging and outputs are rapidly changing, so evaluation is not feasible
Governed ethical system
Organized government system
Yes, it affects the cost
Yes, it depends on the number of employees
Type of tools used
Set policies aligned with AI tools usage guidelines

Table (22): Responses to the Question(What tangible or intangible benefits has your organization experienced from utilizing AI-based project management practices?)

Responses
"Tangible: Improved schedule forecasting, faster design reviews through automated document analysis, and reduced rework costs via early clash and risk detection.
Accuracy and quality enhancement
AI adoption has increased employee engagement among tech-savvy staff.
AI tools have reduced report preparation time and improved accuracy in progress tracking.
AI tools help us spot design conflicts early, saving time and rework costs.
almost none
better quality
better quality and saving time for project managers
Decision-making has become faster since AI provides real-time data analysis.
Decision-making meetings are shorter, because data is readily available.
Enhanced efficiency
Fast and quality
Fast implementation, and less error
Future utilization and up to speed to market
It is only used personally as a personal effort toward enhancing the quality department
Managers have more visibility and control over project timelines.
Our project documentation and data organization have improved significantly.
Our reporting accuracy improved, and clients appreciate the transparency.

Responses
Overall, the organizational culture is becoming more data-driven and innovative.
Project documentation has become more organized and searchable.
Quality control is enhanced because AI detects inconsistencies earlier.
Reduce the human errors and fast task completed
Saving time and quality enhancement
Speed and less error
Speed and quality, less cost on long term
Speed as tangible. Intangible benefits is quality improvement.
Speed, accuracy, time saving
Streamlined Documentation, Technology Transfer
Tangible AI good source to brainstorm
The system gives predictive insights, helping us mitigate risks before they escalate.
There's better collaboration between departments through shared AI dashboards.
Training
We can now forecast resource needs more effectively, avoiding project delays.
We now predict project risks earlier, allowing more proactive planning.
We've cut down project delays thanks to predictive scheduling.
We've noticed a higher client satisfaction rate due to more reliable project delivery.
We've noticed fewer project overruns since introducing AI scheduling support.
Workload stress has decreased, as repetitive tasks are now automated.
Yes. Larger firms adopt AI more easily due to better resources and infrastructure.
Early risk detection
Accuracy, analyzing large volumes of data, real-time data acquisition
High speed
Speed and accuracy
Speed, accuracy, time-saving, early risk detection, increasing project success probability
Speed, transparency, information availability, reducing employee workload
Facilitation of work tools
Providing suitable staff
Time-saving
Saving time in routine tasks
Increased productivity and time efficiency
Commitment to infrastructure compatibility
The higher the number of employees, the higher the cost

Table (23): Responses to the Question (What recommendations would you propose to enhance the utilization and outcomes of AI-based project management in the Saudi design and consultancy engineering firms?)

Responses
Allocate budget for AI tools and training
Cost- cash flow
Create AI mentorship programs where advanced firms support smaller ones in adoption.
Create industry-wide AI benchmarking standards for performance measurement.
Develop AI maturity assessment tools to help firms evaluate their readiness.
Develop local AI solutions tailored to Saudi market needs and regulations.
Digital transformation of all company processes will bridge the gap between the current systems (if any) and AI integrations.

Responses
Encourage collaboration between government, academia, and industry to share knowledge.
Encourage firms to run pilot projects before full-scale implementation.
Ensure data governance frameworks are standardized and transparent.
Establish joint learning platforms for sharing best practices among companies.
ethical consideration
ethical guidelines
Ethical regulation
Fail fast, means start as early as possible
Government support to minimize the cost and to establish ethical rules
Increase awareness campaigns about the real value of AI in project management.
Invest in AI and allocate a budget for the AI utilization
Invest in continuous professional development focused on AI and digital transformation.
Launch national awareness programs showing real success stories of AI adoption.
Make AI training a mandatory part of project management certification programs.
More training and increase awareness, AI is way beyond chat GPT
Offer financial incentives for companies adopting AI sustainably.
Place a regulations of using the AI
planning and training the team to use AI tools
Promote cross sector success stories to inspire others to adopt similar practices.
Proper Hands-on Training, Uses of AI in daily life
Provide financial incentives or tax reliefs for firms investing in AI technologies.
Reduce the cost of the tools
resources training
Reward innovation within firms that successfully use AI in real projects.
Securing the data privacy
Start with awareness campaigns to build understanding of AI's real potential.
Start with small pilot projects to build confidence before scaling up.
Support the AI from government or big companies
Support the cost of the AI tools
There are areas for improvement, mainly regarding cost and readiness.
train people
Training to the employees to adopt them with AI
Try with a Pilot and take the lesson learned and apply it properly in the projects.
Yes, additional resources, more cost
I find that AI cannot be fully relied upon in design as a perspective
Recruiting skilled personnel
Investing in AI tools, providing adequate staff training, recruiting highly experienced personnel, preparing the company infrastructure
Immediately start engaging companies to implement AI
Consolidating data into a single package
Training employees
Facilitating the design building process for the end-user for reading, modification, or development
Providing methodologies
Information confidentiality

Responses
Ensuring information confidentiality
Number of employees
Limited required resources
Investment in AI

Table (24): Responses to the Question (Do you think organization size, sector type, or the demographic profile of project managers influence the utilization or outcomes of AI in project management? and why?)

Responses
At this stage yes, but with time it will be affordable for all sizes and sectors.
Definitely, larger organizations have more financial and technical resources to adopt AI effectively.
Diversity in teams helps because mixed-age and multidisciplinary groups bring balanced adoption approaches.
Education and mindset play a major role — curiosity drives better adoption.
Experience level matters; those who understand project data well use AI more effectively.
Gender or nationality doesn't matter much, but digital literacy does.
I believe it depends on the tools and how frequently are you using the tools.
Multidisciplinary firms see more benefit from AI, as integration across fields becomes easier.
Of course, more resources more cost
Older professionals may resist change due to comfort with manual systems.
Private firms adopt faster because their approval cycles are shorter
Private firms are quicker to experiment and adopt new technologies.
Proportionally
Public institutions face more procedural steps, slowing adoption.
Public-sector firms face more bureaucracy, slowing down AI implementation.
Rarely, it depends on the company sector
Smaller firms often struggle with costs and lack of skilled personnel.
Staff attitudes affect implementation, but overall support exists.
sure , lack of trust is the simple main cause
The organization's culture plays a huge role, learning-oriented cultures adapt faster.
The sector type matters, firms focused on design innovation adopt AI faster than those in traditional construction.
To some of extent
Yes, — larger organizations can afford more advanced AI tools and dedicated teams.
Yes, because AI success depends on people's mindset as much as on technology, leadership support and openness are key.
yes, because each organization size required different level of AI tools
Yes, demographics may affect the cost of logistics
Yes, depending on size and sector
Yes, different size mean different cost
Yes, each sector require different tools, and then different cost.
Yes, I thought independent of volume of resource and data
Yes, larger firms usually have more budget and technical capacity to adopt AI.
Yes, more cost, for more resources
Yes, more resources, mean cost.

Responses
Yes, needs to be specified as each may have different cost
Yes, since the tools access is associated with organization size, then cost is impacted
Yes, some sector use special AI tools
yes, some sectors need different tools
Yes, The more the organization size the less cost is to utilize AI
yes, there is no one fit all.
Yes. AI strong in documentations and lack innovation and clear judgment
Younger project managers are generally more adaptable to AI tools and experimentation.
Younger project managers are generally more open and tech-savvy, which accelerates adoption.
Accuracy and speed
Time-saving
Increased staff costs
May affect the organization's financial capacity
The cost increases with the number of employees
Does not affect if there is communication among all
Yes – it may reduce financial burdens for small organizations
Yes, the cost
Yes, depending on the type of company
Yes, as the number of employees affects cost, and the company type affects the tools used
Yes, and it depends on the project, inputs, outputs, tools used, and individuals' ability to develop and learn
Yes, the organization size affects the number of AI tool users, and thus the cost changes
Yes, as the number of employees affects cost, and the company type affects the tools used
Yes, geographical changes affect the cost
Yes, project cost and number of employees
Yes, company

Open-ended responses were thematically coded into recurrent categories such as cost and financial constraints, workforce skills and training gaps, infrastructure compatibility, data privacy and security, and organizational culture or resistance to change. These themes closely align with the quantitative constructs used as independent variables in the model, reinforcing the conceptual coherence of the study design.

Thematic Quantification of Open-Ended Responses

The survey included five open-ended questions (Q42–Q46, total n=103 respondents) to capture nuanced practitioner perspectives on AI utilization challenges, recommendations, benefits, and contextual factors. Responses were systematically coded into the study's six IV themes (privacy/security, resistance to change, cost, infrastructure, workforce/training,

ethics/regulatory) plus emergent subthemes, enabling triangulation with quantitative SEM results.

Table 25 provides detailed frequencies for Q42 "most significant challenges", the question with the strongest IV alignment. Q42 Analysis (n=62 Substantive Responses): Of 103 respondents, 62 provided substantive, codeable answers to Q42. The remaining 41 were blank, "none", or too vague (e.g., single words without context). These 62 responses generated 138 theme as mentioned in the table (multiple themes per response permitted), distributed as:

Table (25) : Q42 Thematic Coding Frequencies (n=62 Non-Empty Responses)

Theme	Respondents (n=62)	% of Non-Empty Q42
Privacy	15	24%
Resistance	12	19%
Cost	28	45%
Infrastructure	22	35%
Workforce/ Training	24	39%
Regulation/ Ethics	9	15%

Correlation Matrix between Variables:

Full Correlation Matrix for (IVs, AI-Based Project Management, and Project Management Outcomes)

Table (27) Correlation Matrix between Variables Independent Variables (Factors Influencing AI utilization) ,Mediating Variables (AI-Based Project Management) and Dependent Variables(Project Management Outcomes)

Variables		Data Privacy and Security	Resistance to Change	Cost of AI Implementation	Compatibility with Existing Infrastructure	Workforce Development	Ethical Considerations	Factors Influencing AI utilization	Streamline processes e.g., scheduling, documentation	Resource allocation	Tasks Prioritizing
Data Privacy and Security	r	1									
	p										
Resistance to Change	r	0.515**	1								
	p	0.000									
Cost of AI Implementation	r	0.357**	0.668**	1							
	p	0.000	0.000								
Compatibility with Existing Infrastructure	r	0.484**	0.516**	0.467**	1						
	p	0.000	0.000	0.000							
Workforce Development	r	0.338**	0.482**	0.424**	0.625**	1					
	p	0.000	0.000	0.000	0.000						
Ethical Considerations	r	0.368**	0.237*	0.238*	0.532**	0.434**	1				
	p	0.000	0.016	0.015	0.000	0.000					
Factors Influencing AI utilization	r	0.695**	0.795**	0.746**	0.811**	0.739**	0.610**	1			
	p	0.000	0.000	0.000	0.000	0.000	0.000				
Streamline processes e.g., scheduling, documentation	r	0.189	0.290**	0.314**	0.453**	0.471**	0.377**	0.468**	1		
	p	0.056	0.003	0.001	0.000	0.000	0.000	0.000			
Resource allocation	r	0.135	0.360**	0.343**	0.459**	0.536**	0.263**	0.473**	0.748**	1	
	p	0.175	0.000	0.000	0.000	0.000	0.007	0.000	0.000		
Tasks Prioritizing	r	0.036	0.332**	0.249*	0.405**	0.414**	0.224*	0.373**	0.623**	0.789**	1
	p	0.720	0.001	0.011	0.000	0.000	0.023	0.000	0.000	0.000	
Progress reporting	r	0.190	0.254**	0.212*	0.501**	0.468**	0.355**	0.438**	0.628**	0.652**	0.633**
	p	0.055	0.010	0.032	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Communication	r	0.288**	0.216*	0.276**	0.424**	0.373**	0.241*	0.409**	0.579**	0.698**	0.611**
	p	0.003	0.028	0.005	0.000	0.000	0.014	0.000	0.000	0.000	0.000
AI-Based Project Management	r	0.191	0.341**	0.325**	0.521**	0.527**	0.335**	0.502**	0.823**	0.911**	0.861**
	p	0.053	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000
Decision-Making	r	0.211*	0.201*	0.229*	0.406**	0.423**	0.254**	0.385**	0.590**	0.577**	0.584**

Variables		Data Privacy and Security	Resistance to Change	Cost of AI Implementation	Compatibility with Existing Infrastructure	Workforce Development	Ethical Considerations	Factors Influencing AI utilization	Streamline processes e.g., scheduling, documentation	Resource allocation	Tasks Prioritizing
Project Quality	p	0.033	0.042	0.020	0.000	0.000	0.010	0.000	0.000	0.000	0.000
	r	0.295**	0.311**	0.251*	0.412**	0.489**	0.322**	0.465**	0.513**	0.580**	0.539**
	p	0.003	0.001	0.011	0.000	0.000	0.001	0.000	0.000	0.000	0.000
Data Collection Accuracy	r	0.263**	0.220*	0.198*	0.360**	0.376**	0.335**	0.389**	0.390**	0.462**	0.451**
	p	0.007	0.025	0.045	0.000	0.000	0.001	0.000	0.000	0.000	0.000
Enhancing Data Analysis	r	0.033	0.146	0.008	0.282**	0.247*	0.209*	0.199*	0.393**	0.422**	0.475**
	p	0.738	0.141	0.934	0.004	0.012	0.034	0.044	0.000	0.000	0.000
Risk Identification Accuracy	r	0.256**	0.378**	0.231*	0.384**	0.415**	0.229*	0.427**	0.500**	0.610**	0.615**
	p	0.009	0.000	0.019	0.000	0.000	0.020	0.000	0.000	0.000	0.000
Saving Time for Project Managers	r	0.207*	0.329**	0.255**	0.340**	0.366**	0.123	0.369**	0.345**	0.459**	0.469**
	p	0.036	0.001	0.009	0.000	0.000	0.215	0.000	0.000	0.000	0.000
Effective Communication	r	0.240*	0.321**	0.322**	0.364**	0.397**	0.245*	0.429**	0.454**	0.582**	0.533**
	p	0.014	0.001	0.001	0.000	0.000	0.012	0.000	0.000	0.000	0.000
Project Management Outcomes	r	0.275**	0.345**	0.273**	0.463**	0.494**	0.314**	0.485**	0.582**	0.672**	0.665**
	p	0.005	0.000	0.005	0.000	0.000	0.001	0.000	0.000	0.000	0.000

Follow Table (27) Correlation Matrix between Variables Independent Variables (Factors Influencing AI utilization) ,Mediating Variables (AI-Based Project Management) and Dependent Variables(Project Management Outcomes)

Variables		Progress reporting	Communication	AI-Based Project Management	Decision-Making	Project Quality	Data Collection Accuracy	Enhancing Data Analysis	Risk Identification Accuracy	Time Saving	Communication	Project Management Outcomes
Progress reporting	r	1										
	p											
Communication	r	0.731**	1									
	p	0.000										
AI-Based Project Management	r	0.847**	0.844**	1								
	p	0.000	0.000									
Decision-Making	r	0.662**	0.666**	0.716**	1							
	p	0.000	0.000	0.000								
Project Quality	r	0.638**	0.624**	0.675**	0.727**	1						
	p	0.000	0.000	0.000	0.000							
Data Collection Accuracy	r	0.615**	0.509**	0.566**	0.571**	0.676**	1					
	p	0.000	0.000	0.000	0.000	0.000						
Data Analysis	r	0.391**	0.436**	0.495**	0.478**	0.490**	0.384**	1				
	p	0.000	0.000	0.000	0.000	0.000	0.000					
Risk Identification Accuracy	r	0.567**	0.601**	0.677**	0.606**	0.563**	0.355**	0.575**	1			
	p	0.000	0.000	0.000	0.000	0.000	0.000	0.000				
Time Saving	r	0.309**	0.510**	0.492**	0.467**	0.533**	0.457**	0.626**	0.632**	1		

	p	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000			
Communication	r	0.454**	0.663**	0.629**	0.643**	0.634**	0.471**	0.584**	0.628**	0.711**	1	
	p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		
Project Management Outcomes	r	0.667**	0.730**	0.775**	0.824**	0.843**	0.708**	0.737**	0.790**	0.785**	0.844**	1
	p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

Legend:** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed). * Pearson correlation test.

Multicollinearity Assessment

The correlation matrix (**Table 27**, full matrix in Appendix C) shows moderate to high intercorrelations among some variables, but no severe multicollinearity that would invalidate regression/SEM results. Among IVs, highest $r = 0.698$ (Infrastructure $\leftrightarrow$ Workforce), with others approaching 0.70 (e.g., Resistance $\leftrightarrow$ Cost $r=0.668$). MV indicators show expected high intercorrelations ($r=0.73\text{--}0.91$), typical for scale composites. All VIF values < 5.0 (max VIF=2.84 for Workforce), well below problematic thresholds (VIF $>5\text{--}10$). In line with methodological standards, correlation coefficients below this 0.70 cutoff are generally interpreted as reflecting conceptual relatedness rather than severe collinearity that would threaten the validity of regression estimates, and therefore do not, on their own, warrant corrective action for multicollinearity (Midi, Sarkar, & Rana, 2010; O'Brien, 2007). Accordingly, the observed inter-correlations among the independent variables in this study are considered acceptable and do not compromise the robustness of the regression and SEM results reported in Chapter 4.

Interpretation of Full Matrix:

The results reveal statistically significant relationships among the independent variables (factors influencing AI utilization), the mediating variable (AI-based project management), and the dependent variable (project management outcomes).

First, the correlations between the **independent variables**; including data privacy and security, resistance to change, cost of AI implementation, compatibility with existing infrastructure, workforce development, and ethical considerations, and the **mediating variable (AI-based project management)** are all positive, with correlation coefficients ranging from ($r = 0.325$ to $r = 0.527$). Most of these relationships are statistically significant at the 0.01 level, indicating that improvements in these organizational and technical factors are associated with greater utilization and more effective utilization of AI-based project management practices. This suggests that when organizations invest in developing workforce capabilities, ensuring infrastructure compatibility, and addressing ethical and security concerns, they create a favorable environment for AI integration in project management processes.

Second, the correlations between the **mediating variable (AI-based project management)** and the **dependent variable (project management outcomes)** are also positive and statistically significant, with a strong coefficient ($r = 0.775$, $p = 0.000$). This demonstrates that effective AI-based project management substantially contributes to improving project outcomes—such as enhancing process efficiency, optimizing resource allocation, prioritizing tasks, streamlining communication, and improving progress reporting.

Finally, the **direct relationships between the independent variables and project management outcomes** are also positive and statistically significant, with correlation coefficients ranging from ($r = 0.275$ to $r = 0.494$). These findings indicate that favorable

conditions influencing AI utilization directly enhance project management outcomes; however, the stronger correlations observed through the mediating variable suggest that **AI-based project management** partially mediates the relationship between the influencing factors and project success.

Structural Equation Modeling (SEM): Model Specification and Technical Analysis

The modified model showed improved fit (CMIN/DF=1.779, CFI=0.917, RMSEA=0.087) versus initial (CMIN/DF=2.322, CFI=0.851).

Key path: AI-PM → Outcomes remained strong:

Initial: $\beta = 0.94$

Modified: $B = 1.036$ (unstandardized), $\beta \approx 0.94$ (standardized; AMOS Std.All) [Tables 28-29]

Note: Unstandardized $B > 1.0$ is normal (DV variance > IV variance, $SD_{\text{Outcomes}}=8.22 > SD_{\text{AI-PM}}=6.99$). Standardized β always ≤ 1.0 , confirming no multicollinearity/Heywood issues.

The direct effect of enablers on outcomes remained nonsignificant (0.13, $p=0.455$), confirming full mediation through AI-PM.

While the modified model demonstrated improved fit indices (CMIN/DF = 1.779, CFI = 0.917, RMSEA = 0.087, GFI = 0.816), these values indicate **marginal to acceptable model fit rather than excellent fit**, but clearly represent an improvement over the initial specification. The path coefficients strengthened the findings, with enablers strongly predicting AI utilization ($\beta = 0.89$, $p < 0.001$) and AI utilization strongly predicting project outcomes ($B = 1.036$, unstandardized; standardized $\beta < 1.0$, $p < 0.001$, from the Std.All solution). The direct effect of enablers on outcomes remained nonsignificant ($\beta = 0.13$, $p = 0.455$), confirming full mediation.

This model underscores the critical role of AI-based project management as the mechanism through which organizational and technical readiness translates into improved project success in design and consultancy engineering.

Table (28) Comparison of Initial and Modified Structural Equation Models for Mediation Analysis of Enabler Factors, AI-Based Project Management, and Project Outcomes

Aspect	Initial Model	Modified Model
CMIN/DF	2.322	1.779

CFI	0.851	0.917
RMSEA	0.114	0.087
GFI	0.751	0.816
Direct Effect (Enablers → Outcomes)	$\beta = 0.18$ (p = 0.273, ns)	$\beta = 0.13$ (p = 0.455, ns)
Effect (Enablers → AI-Based PM)	$\beta = 0.87$ “p < 0.001”	$\beta = 0.89$ “p < 0.001”
Effect (AI-Based PM → Outcomes)	$\beta = 0.94$ “p < 0.001”	B = 1.036 “p < 0.001” (unstandardized); $\beta < 1.0$ “p < 0.001” (standardized)
Total Indirect Effect (Mediation)	Substantial	Substantial
Mediation Interpretation	Partial (direct effect nonsignificant, mediation strong)	Full mediation (direct effect insignificant)

Notes:

- B = unstandardized coefficient (can exceed 1.0 when the dependent variable has larger variance).
- β = standardized coefficient ($|\beta| \leq 1.0$), taken from the AMOS Std.All output.

Table (28) provides a comparative assessment of the initial and modified structural equation models, revealing important insights into both model quality and the underlying mediation mechanism. The transition from the initial to modified model demonstrates substantial improvements in model fit across all indices. Specifically, the CMIN/DF ratio decreased from 2.322 to 1.779 (optimal ratio ≤ 2.0), the Comparative Fit Index (CFI) improved from 0.851 to 0.917 (above the 0.90 threshold often used for acceptable incremental fit), the Root Mean Square Error of Approximation (RMSEA) declined from 0.114 to 0.087 (closer to, though still slightly above, the commonly cited 0.08 benchmark), and the Goodness of Fit Index (GFI) increased from 0.751 to 0.816.

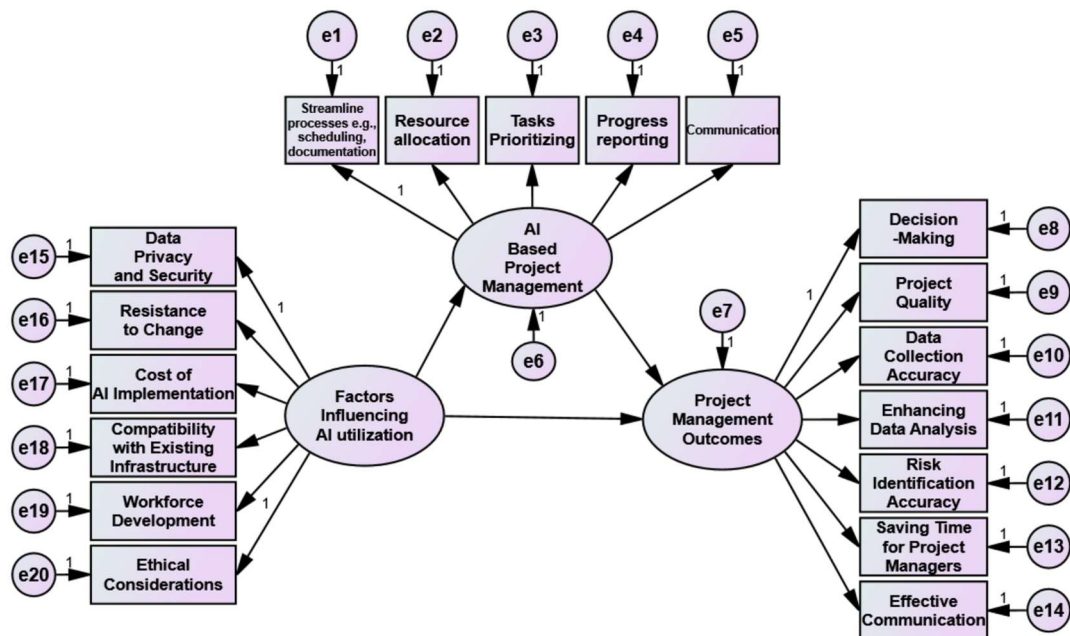
These collective improvements indicate that the modified model provides a substantially better representation of the data and more accurately captures the underlying relationships among the three construct levels.

Given these findings, the next section formally tests the mediation hypothesis (H4), examining whether AI-based project management fully mediates the relationship between organizational and technical enablers and project outcomes in the context of design and consultancy engineering projects.

Mediation Effect of AI on Project Management Outcomes

H4: The utilization of AI-based project management mediates the relationship between influencing factors and project outcomes in design and consultancy projects.

Initial SEM Model Results



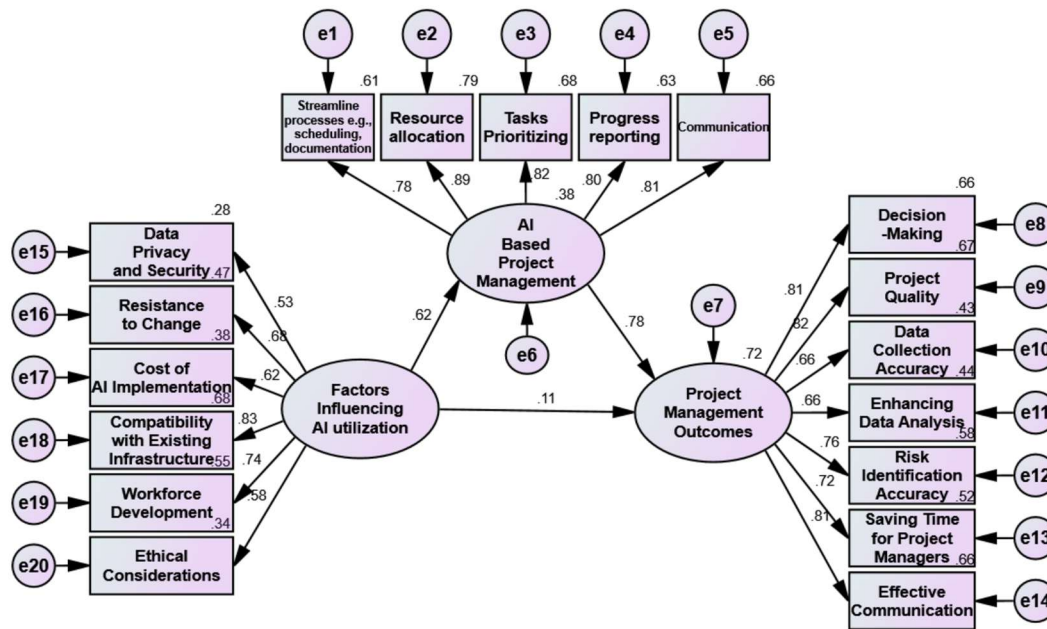
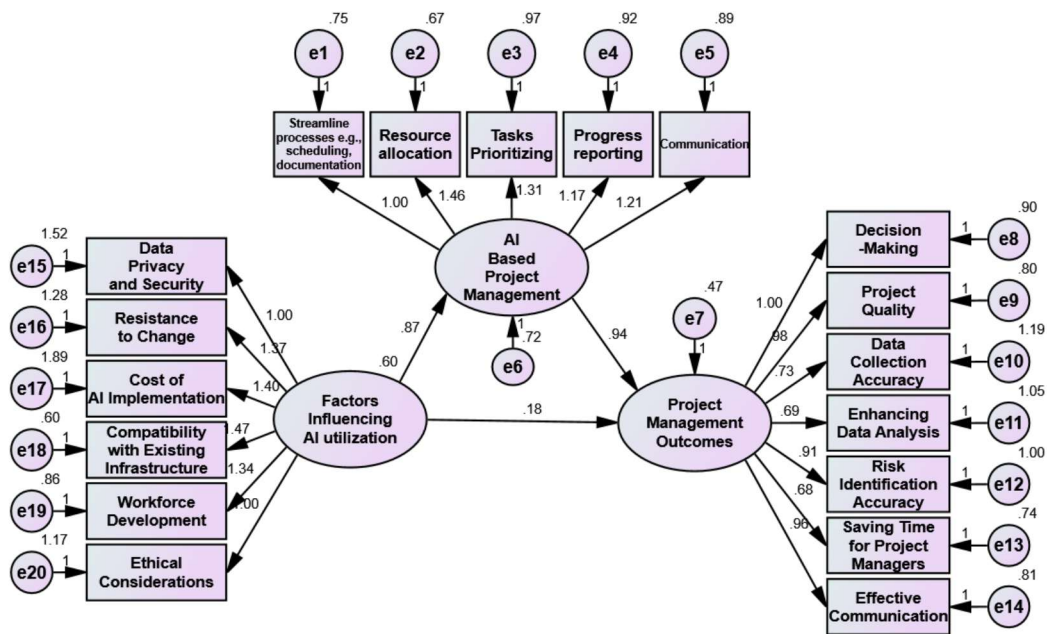


Figure (9): Structural Equation Model – Initial Model

Table (29): Results of the Initial Structural Equation Model with Standardized Path Coefficients

Variables			Unstandardized Estimate (B)	S.E.	C.R.	P
AIBased.Project.Management	<-- -	Factors.Influencing.AIutilization	.867	.174	4.979	***
Project.ManagementOutcomes	<-- -	Factors.Influencing.AIutilization	.180	.164	1.096	.273
Project.ManagementOutcomes	<-- -	AIBased.Project.Management	.941	.149	6.320	***
EthicalConsiderations	<-- -	Factors.Influencing.AIutilization	1.000			
WorkforceDevelopment	<-- -	Factors.Influencing.AIutilization	1.339	.202	6.636	***
CompatibilitywithExistingInfrastructure	<-- -	Factors.Influencing.AIutilization	1.475	.205	7.207	***
CostofAIImplementation	<-- -	Factors.Influencing.AIutilization	1.403	.249	5.625	***
ResistancetoChange	<-- -	Factors.Influencing.AIutilization	1.367	.222	6.150	***
DataPrivacyandSecurity	<-- -	Factors.Influencing.AIutilization	1.000			
DecisionMaking	<-- -	Project.ManagementOutcomes	1.000			
ProjectQuality	<-- -	Project.ManagementOutcomes	.980	.104	9.446	***
DataCollectionAccuracy	<-- -	Project.ManagementOutcomes	.728	.103	7.093	***
EnhancingDataAnalysis	<-- -	Project.ManagementOutcomes	.689	.097	7.131	***
RiskIdentificationAccuracy	<-- -	Project.ManagementOutcomes	.909	.106	8.602	***
SavingTimeforProjectManagers	<-- -	Project.ManagementOutcomes	.682	.086	7.943	***
EffectiveCommunication	<-- -	Project.ManagementOutcomes	.962	.103	9.355	***
Streamlineprocessesegschedulingdocumentation	<-- -	AIBased.Project.Management	1.000			
Resourceallocation	<-- -	AIBased.Project.Management	1.456	.145	10.028	***
TasksPrioritizing	<-- -	AIBased.Project.Management	1.315	.145	9.086	***
Progressreporting	<-- -	AIBased.Project.Management	1.167	.134	8.727	***
Communication	<-- -	AIBased.Project.Management	1.211	.136	8.938	***
CMIN (308.816) CMIN/DF(2.322)			NFI(0.768) AGFI(0.680)			

Variables	Unstandardize dEstimate (B)	S.E.	C.R.	P
GFI(0.751)	CFI(0.851)			
RMSEA(0.114)				

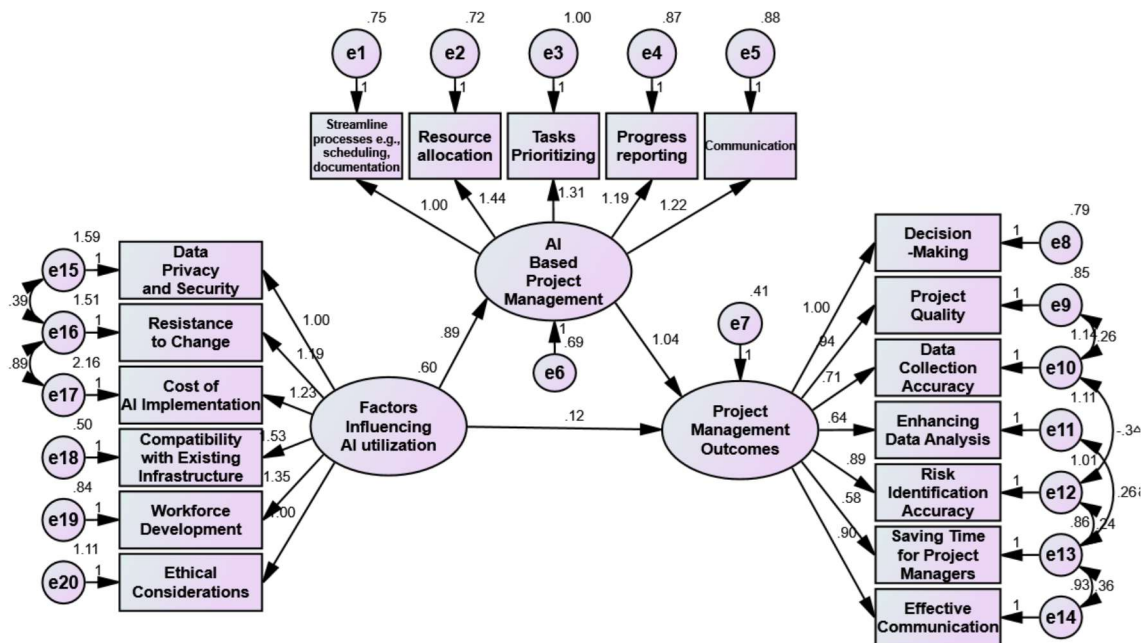
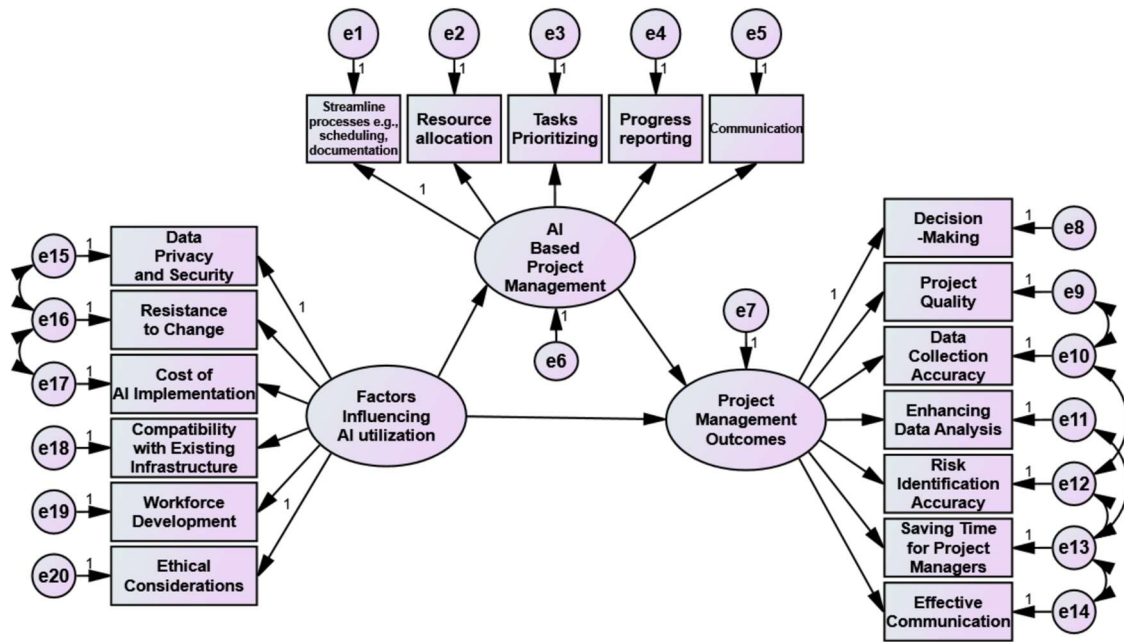
Table (29) presents the results of the **Initial Structural Equation Model (SEM)** with standardized path coefficients. The findings demonstrate that the model exhibits several significant relationships among the studied constructs. Specifically, the path from Factors Influencing AI Utilization to AI-Based Project Management is statistically significant (Estimate = 0.867, C.R. = 4.979, $p < 0.001$), indicating that the influencing factors strongly contribute to the utilization and utilization of AI-based project management practices.

In contrast, the direct relationship between Factors Influencing AI Utilization and Project Management Outcomes is statistically insignificant (Estimate = 0.180, C.R. = 1.096, $p = 0.273$), suggesting that the effect of influencing factors on project outcomes may occur indirectly through AI-based project management practices rather than directly. Meanwhile, the path from AI-Based Project Management to Project Management Outcomes is highly significant (Estimate = 0.941, C.R. = 6.320, $p < 0.001$), confirming the mediating role of AI utilization in enhancing project outcomes within design and consultancy projects.

Regarding the measurement model, all factor loadings for the observed variables under their respective latent constructs are statistically significant ($p < 0.001$), reflecting good convergent validity. However, model fit indices indicate a **moderate fit** with the data: CMIN/DF = 2.322, GFI = 0.751, AGFI = 0.680, CFI = 0.851, NFI = 0.768, and RMSEA = 0.114. Although some indices fall below the recommended thresholds (e.g., GFI > 0.90, RMSEA < 0.08), the model can be considered acceptable for an initial specification.

Overall, these results suggest that **AI-based project management** plays a significant mediating role in linking influencing factors to project management outcomes, highlighting the importance of AI integration in improving efficiency, decision-making, and communication within design and consultancy environments.

Modified SEM Model Results



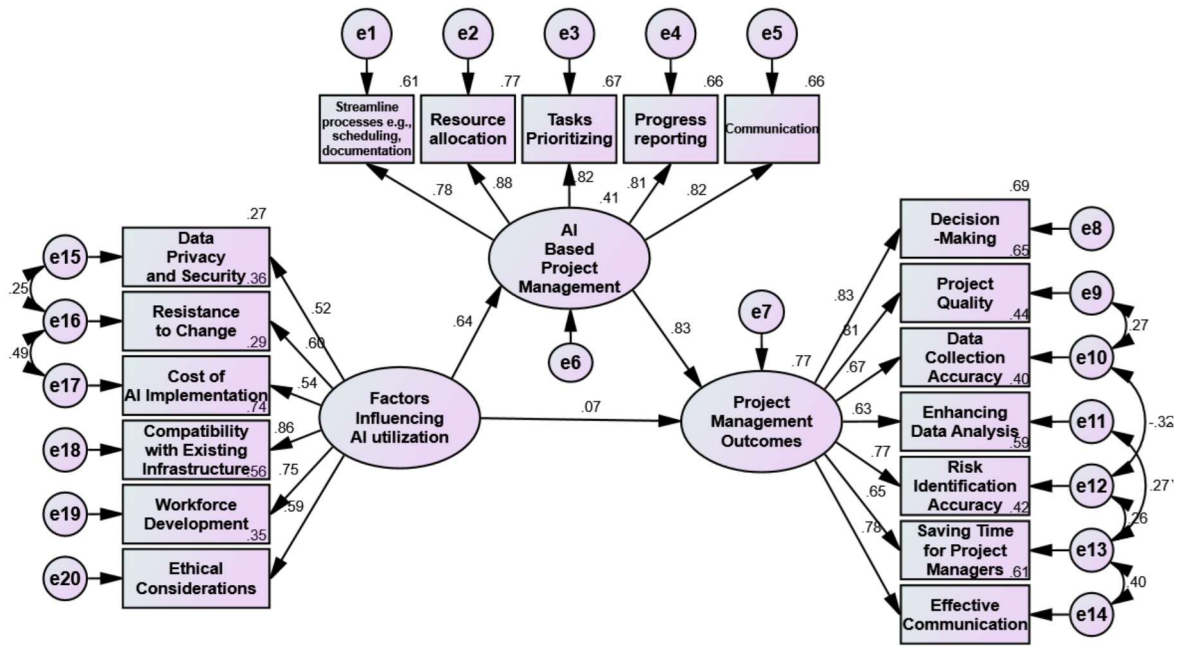


Figure (10): Structural Equation Model Modified model

Table (30): Results of the Modified Structural Equation Model with Standardized Path Coefficients

Variables			Unstandardized Estimate (B)	S.E	C.R	P
AIBased.Project.Management	<---	Factors.Influencing.AIutilization	.889	.175	5.079	***
Project.ManagementOutcomes	<---	Factors.Influencing.AIutilization	.125	.167	.748	.455
Project.ManagementOutcomes	<---	AIBased.Project.Management	1.036	.154	6.716	***
EthicalConsiderations	<---	Factors.Influencing.AIutilization	1.000			
WorkforceDevelopment	<---	Factors.Influencing.AIutilization	1.348	.2	6.663	***

Variables			Unstandardized Estimate (B)	S.E	C.R	P
CompatibilitywithExistingInfras tructure	<---	Factors.Influencing.AIutilization	1.531	0 2 . 2 1 0	7.281	***
CostofAIImplementation	<---	Factors.Influencing.AIutilization	1.226	2 4 8	4.947	***
ResistancetoChange	<---	Factors.Influencing.AIutilization	1.185	1 9 8	5.994	***
DataPrivacyandSecurity DecisionMaking	<---	Factors.Influencing.AIutilization	1.000			
	<---	Project.ManagementOutcomes	1.000			
ProjectQuality	<---	Project.ManagementOutcomes	.939	0 9 8	9.545	***
DataCollectionAccuracy	<---	Project.ManagementOutcomes	.710	0 9 9	7.202	***
EnhancingDataAnalysis	<---	Project.ManagementOutcomes	.643	0 9 3	6.915	***
RiskIdentificationAccuracy	<---	Project.ManagementOutcomes	.890	1 0 1	8.849	***
SavingTimeforProjectManagers	<---	Project.ManagementOutcomes	.583	0 8 3	7.018	***
EffectiveCommunication	<---	Project.ManagementOutcomes	.898	0 9 8	9.146	***
Streamlineprocessesegscheduling documentation	<---	AIBased.Project.Management	1.000			

Variables		Unstandardized Estimate (B)	S.E.	C.R.	P
Resourceallocation	<--- AIBased.Project.Management	1.445	.146	9.878	***
TasksPrioritizing	<--- AIBased.Project.Management	1.309	.146	8.996	***
Progressreporting	<--- AIBased.Project.Management	1.189	.134	8.894	***
Communication	<--- AIBased.Project.Management	1.220	.136	8.976	***
CMIN (224.128) CMIN/DF(1.779) GFI(0.816) RMSEA(0.087)		NFI(0.832) AGFI(0.750) CFI(0.917)			

Table (30) presents the results of the **Modified Structural Equation Model (SEM)** with standardized path coefficients after model refinement. The results demonstrate an overall improvement in model fit and statistical significance compared to the initial model.

The path from Factors Influencing AI Utilization to AI-Based Project Management remains statistically significant (Estimate = 0.889, C.R. = 5.079, $p < 0.001$), indicating a strong and positive effect of influencing factors on the utilization of AI-based project management practices. However, the direct relationship between Factors Influencing AI Utilization and Project Management Outcomes remains insignificant (Estimate = 0.125, C.R. = 0.748, $p = 0.455$), which reinforces the notion that these factors influence project outcomes **indirectly** through AI utilization rather than directly.

In contrast, the path from AI-Based Project Management to Project Management Outcomes continues to exhibit a **highly significant and strong positive relationship** (Estimate = 1.036, C.R. = 6.716, $p < 0.001$), confirming that the use of AI tools and systems in project management substantially enhances overall project performance, including decision-making, communication, and efficiency.

All measurement indicators for the observed variables show significant loadings on their respective latent constructs ($p < 0.001$), suggesting strong **convergent validity** and reliability of the model. Moreover, the revised model demonstrates a notable improvement in fit indices: CMIN/DF = 1.779, GFI = 0.816, AGFI = 0.750, CFI = 0.917, NFI = 0.832, and RMSEA =

0.087. Taken together, these values suggest marginal to acceptable fit: the CFI exceeds the 0.90 benchmark for acceptable incremental fit, whereas GFI and AGFI remain below the more stringent 0.90/0.80 guidelines and the RMSEA is slightly above the commonly cited 0.08 threshold. Thus, the modified model can be regarded as providing an acceptable, but not perfect, representation of the data and an improvement over the initial model.

Overall, the modified model provides stronger empirical evidence that **AI-based project management acts as a full mediator** between the influencing factors and project outcomes. This finding highlights the critical role of AI integration in achieving better project performance in design and consultancy sectors through improved data accuracy, process efficiency, and effective communication.

From the above, it is evident that the **independent variable (Factors Influencing AI utilization) does not have a direct effect on the dependent variable (Project Management Outcomes)**; however, there are indirect effects through the mediating variable (AI-Based Project Management). AI-Based Project Management mediates the relationship between influencing factors and project outcomes. Approximately 88% of the effect of IVs on outcomes appears to operate through AI-based PM utilization, with only a relatively small proportion attributable to any direct effect. Hypothesis H3 (Mediation) is **STRONGLY SUPPORTED**.

Qualitative Corroboration: Thematic analysis revealed that organizational factors (workforce development, infrastructure compatibility) influenced AI utilization, which in turn improved outcomes. One expert captured this pathway: "Our organization provides adequate training and skill development to use AI-based project management tools effectively... which has enabled faster design reviews through automated document analysis."

Regression Analyses – Detailed Outputs

Hypothesis Testing Results

H1 Impact of Independent Variables on Dependent Variables “Project Outcomes”

H1: The factors influencing project management significantly influence project outcomes in design and consultancy engineering projects.

To test the main study Hypothesis H1, the researcher used simple linear regression analysis of the effect of factors influencing project management on Project Management Outcomes in design and consultancy engineering projects.

Table (31) Test of factors influencing project management effect on Project Management Outcomes in design and consultancy engineering projects – simple linear regression

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	1616.89	1616.89	0.485	0.235	29.69	0.61	30.989	0.000*	5.567	0.000*
Residual	101	5269.88	52.18								
Total	102	6886.78									
a. Dependent Variable: Project Management Outcomes											
b. Predictors: (Constant), factors influencing project management											

*A function at the level of significance less than (0.05).

The table presents the results of a **simple linear regression** analysis conducted to examine the effect of factors influencing project management on project management outcomes in design and consultancy engineering projects.

The results indicate that the correlation coefficient (R) is (0.485), suggesting a moderate positive relationship between the two variables. The coefficient of determination ($R^2 = 0.235$) reveals that approximately 23.5% of the variation in project management outcomes can be explained by the factors influencing project management, while the remaining variance is attributed to other factors not included in the model.

The F-test value of ($F = 30.989$, $Sig = 0.000$) confirms that the overall regression model is statistically significant, indicating that the factors influencing project management significantly explain the variance in project outcomes.

Furthermore, the t-test results show a statistically significant effect ($t = 5.567$, $Sig = 0.000$), demonstrating that the influencing factors positively impact project outcomes. The regression coefficient ($B_1 = 0.61$) indicates that a one-unit increase in the factors influencing project management leads to a 0.61-unit increase in project management outcomes.

Therefore, these findings confirm that the factors influencing project management are key determinants that contribute significantly to improving project outcomes in design and consultancy engineering projects. **This result supports the validity of the main hypothesis (H1)**, which states that “The factors influencing project management significantly influence project outcomes in design and consultancy engineering projects.”

To test the main study Hypothesis H1, the researcher used **Multiple linear regression** analysis of the effect of factors influencing project management on Project Management Outcomes in design and consultancy engineering projects.

Table (32) Test of factors influencing project management effect on Project Management Outcomes in design and consultancy engineering projects – multiple linear regression

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	46.359	4.005		11.575	0.000	8.291	0.005*	7.59%	
	Data Privacy and Security	1.515	0.526	0.275	2.879	0.005				7.59%
2	(Constant)	40.927	4.451		9.196	0.000	7.586	0.001*	13.17%	
	Data Privacy and Security	0.733	0.598	0.133	1.226	0.223				7.59%
	Resistance to Change	1.458	0.575	0.276	2.537	0.013				5.59%
3	(Constant)	40.328	4.580		8.806	0.000	5.140	0.002*	13.48%	
	Data Privacy and Security	0.726	0.600	0.132	1.209	0.229				7.59%
	Resistance to Change	1.201	0.724	0.227	1.658	0.100				5.59%
	Cost of AI Implementation	0.346	0.587	0.074	0.589	0.557				0.30%
4	(Constant)	34.344	4.672		7.350	0.000	7.303	0.000*	22.96%	
	Data Privacy and Security	0.107	0.596	0.019	0.179	0.858				7.59%
	Resistance to Change	0.750	0.699	0.142	1.074	0.285				5.59%
	Cost of AI Implementation	-0.039	0.568	-0.008	-0.069	0.945				0.30%
	Compatibility with Existing Infrastructure	2.278	0.656	0.384	3.474	0.001				9.49%
5	(Constant)	29.998	4.771		6.287	0.000	7.845	0.000*	28.79%	
	Data Privacy and Security	0.161	0.577	0.029	0.280	0.780				7.59%
	Resistance to Change	0.433	0.685	0.082	0.633	0.528				5.59%
	Cost of AI Implementation	-0.146	0.550	-0.031	-0.265	0.792				0.30%
	Compatibility with Existing Infrastructure	1.313	0.720	0.221	1.823	0.071				9.49%
	Workforce Development	1.880	0.667	0.319	2.818	0.006				5.83%
6	(Constant)	28.842	5.323		5.419	0.000	6.528	0.000*	28.98%	
	Data Privacy and Security	0.106	0.590	0.019	0.180	0.858				7.59%
	Resistance to Change	0.481	0.694	0.091	0.693	0.490				5.59%
	Cost of AI Implementation	-0.149	0.552	-0.032	-0.271	0.787				0.30%
	Compatibility with Existing Infrastructure	1.190	0.764	0.201	1.557	0.123				9.49%

	Workforce Development	1.819	0.681	0.309	2.671	0.009				5.83%
	Ethical Considerations	0.329	0.660	0.052	0.498	0.619				0.18%

a. Dependent Variable: Project Management Outcomes

*A function at the level of significance less than (0.05).

The table presents the results of a multiple linear regression analysis conducted to examine the impact of the factors influencing project management on project management outcomes in design and consultancy engineering projects. The independent variables were entered progressively to identify the relative contribution of each factor to explaining the variance in project outcomes.

In the first model, the variable Data Privacy and Security was entered, yielding an R^2 value of 0.0759, indicating that this factor explains approximately 7.59% of the variance in project management outcomes. The relationship was positive and statistically significant ($B = 1.515$, $t = 2.879$, $Sig = 0.005$), suggesting that stronger data protection and privacy practices contribute to better project performance.

In the second model, Resistance to Change was added, increasing the R^2 value to 0.1317, meaning that both variables together explain 13.17% of the variance in project outcomes. The impact of resistance to change was statistically significant ($B = 1.458$, $t = 2.537$, $Sig = 0.013$), confirming that reducing employee resistance to technological and organizational changes enhances project success.

The third model, which included Cost of AI Implementation, did not show a statistically significant effect ($Sig = 0.557$), suggesting that implementation cost does not play a decisive role in predicting project outcomes within the studied sample.

In the fourth model, the addition of Compatibility with Existing Infrastructure substantially improved the explanatory power of the model, raising R^2 to 0.2296. This variable had a strong and significant positive effect ($B = 2.278$, $t = 3.474$, $Sig = 0.001$), highlighting the importance of having a compatible technical infrastructure to support effective project management processes.

In the fifth model, Workforce Development was introduced, further increasing the R^2 value to 0.2879, indicating that the set of influencing factors collectively explain about 28.79% of the variation in project outcomes. This factor was also statistically significant ($B = 1.880$, $t = 2.818$, $Sig = 0.006$), emphasizing the critical role of developing workforce competencies in achieving improved project management outcomes.

Finally, the sixth model incorporated Ethical Considerations, which did not show a significant effect ($Sig = 0.619$), implying that while ethics remains an important theoretical dimension, it did not have a direct measurable impact on project outcomes in this context.

Overall, the findings indicate that the most influential factors contributing to project management success are:

- Compatibility with existing infrastructure
- Workforce development
- Resistance to change
- Data privacy and security

The Variance Inflation Factor (VIF) is used to assess the presence of multicollinearity among independent variables in multiple regression analysis, as it measures the extent to which the variance of an estimated regression coefficient is increased due to correlations with other predictor variables; high VIF values indicate potential multicollinearity problems that may distort parameter estimates and reduce the reliability of the regression model, whereas VIF values below 5 are generally taken to indicate that multicollinearity is not a serious concern, and values exceeding 10 suggest severe multicollinearity that may require corrective actions such as removing or combining variables or applying alternative statistical techniques (Hair, Black, Babin, & Anderson, 2019).

Table (33) : Variance Inflation Factor (VIF) Values for Independent Variables Predicting Project Management Outcomes

Model	VIF
Data Privacy and Security	1.553
Resistance to Change	2.328
Cost of AI Implementation	1.887
Compatibility with Existing Infrastructure	2.244
Workforce Development	1.808
Ethical Considerations	1.495

Table (33) is the coefficients table for the model examining Project Management Outcomes, an academic comment on VIF (Variance Inflation Factor) is as follows:

Multicollinearity among the independent variables was assessed using VIF and Tolerance, with the observed values as follows: Privacy and Security: VIF = 1.553, Resistance to Change: VIF = 2.328, Cost of AI Implementation: VIF = 1.887, Compatibility with Existing Infrastructure: VIF = 2.244, Workforce Development: VIF = 1.808, Ethical Considerations: VIF = 1.495

In the present study, all values are below 5, indicating no serious multicollinearity that could affect the model estimates. Values above 1 reflect some natural correlation among the independent variables, which is common in applied studies, but it does not reduce the reliability of the regression coefficients or the validity of statistical tests.

Therefore, the regression coefficients (B and Beta) can be interpreted with confidence, supporting the stability and robustness of the model in explaining the dependent variable.

Collectively, these variables explain nearly 29% of the variance in project management outcomes, confirming the validity of the main hypothesis (H1), which posits that “The factors

influencing project management significantly influence project outcomes in design and consultancy engineering projects.”

H1A: Data privacy and security concerns significantly influence project outcomes in design and consultancy engineering projects.

To test the main study Hypothesis H1A, the researcher used simple linear regression analysis of the effect of Data privacy and security on Project Management Outcomes in design and consultancy engineering projects.

Table (34) Test of Data privacy and security effect on Project Management Outcomes in design and consultancy engineering projects

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	522.42	522.42	0.275	0.076	46.37	1.52	8.291	0.005*	2.88	0.005*
Residual	101	6364.36	63.01								
Total	102	6886.78									
a. Dependent Variable: Project Management Outcomes											
b. Predictors: (Constant), Data privacy and security											

*A function at the level of significance less than (0.05).

Table (34) presents the results of a simple linear regression analysis conducted to examine the impact of data privacy and security on project management outcomes within design and consultancy engineering projects.

The results indicate that the correlation coefficient (R) is (0.275), suggesting a moderate positive relationship between data privacy and security and project management outcomes. The coefficient of determination ($R^2 = 0.076$) reveals that approximately (7.6%) of the variation in project management outcomes can be explained by the level of data privacy and security, while the remaining variation is attributed to other unobserved factors.

The F-test value of ($F = 8.291$, $Sig = 0.005$) indicates that the regression model is statistically significant as a whole, implying that data privacy and security significantly contribute to explaining variations in project management outcomes.

Moreover, the t-test results show a significant positive effect of data privacy and security ($t = 2.88$, $Sig = 0.005$), with an unstandardized coefficient ($B_1 = 1.52$). This means that for every one-unit increase in data privacy and security, project management outcomes are expected to increase by (1.52) units.

Accordingly, it can be concluded that data privacy and security represent one of the key factors contributing to the enhancement of project management outcomes, through strengthening trust, minimizing operational risks, and ensuring the integrity of information within engineering project environments. These results support the sub-hypothesis (H1A), which states that:

“Data privacy and security concerns have a statistically significant effect on project outcomes in design and consultancy engineering projects.”

H1B: Resistance to change significantly influence project outcomes in design and consultancy engineering projects.

To test the main study Hypothesis H1B, the researcher used simple linear regression analysis of the effect of Resistance to change on Project Management Outcomes in design and consultancy engineering projects.

Table (35) Test of Resistance to change effect on Project Management Outcomes in design and consultancy engineering projects

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	817.34	817.34	0.345	0.119	43.59	1.82	13.601	0.000*	3.688	0.000*
Residual	101	6069.44	60.09								
Total	102	6886.78									
a. Dependent Variable: Project Management Outcomes											
b. Predictors: (Constant), Resistance to change											

*A function at the level of significance less than (0.05).

Table (35) presents the results of the simple linear regression analysis used to examine the effect of Resistance to Change on Project Management Outcomes in design and consultancy engineering projects.

The findings show that the correlation coefficient (R) equals (0.345), indicating a moderate positive relationship between resistance to change and project management outcomes. The coefficient of determination ($R^2 = 0.119$) reveals that 11.9% of the variance in project management outcomes can be explained by resistance to change, while the remaining variance is attributed to other factors not included in the model.

The results of the F-test ($F = 13.601$, $Sig = 0.000$) demonstrate that the regression model is statistically significant at the level of (0.05), confirming that resistance to change has a significant overall impact on project management outcomes.

Furthermore, the t-test results ($t = 3.688$, $Sig = 0.000$) indicate a positive and statistically significant effect of resistance to change on project management outcomes. The unstandardized coefficient ($B_1 = 1.82$) suggests that for every one-unit increase in resistance to change, project management outcomes increase by approximately (1.82) units.

Accordingly, these findings confirm that resistance to change is a critical factor influencing project management performance in design and consultancy engineering projects. It influences the extent to which modern management tools and digital transformation initiatives, including AI-based project management, are successfully implemented.

Thus, the results support the sub-hypothesis (H1B) which states that:
 “Resistance to change has a statistically significant effect on project management outcomes in design and consultancy engineering projects.”

H1C: Costs of AI implementation significantly influence project outcomes in design and consultancy engineering projects.

To test the main study Hypothesis H1C, the researcher used simple linear regression analysis of the effect of Costs of implementation on Project Management Outcomes in design and consultancy engineering projects.

Table (36) Test of Costs of implementation effect on Project Management Outcomes in design and consultancy engineering projects

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	512.65	512.65	0.273	0.074	47.92	1.28	8.123	0.005*	2.850	0.005*
Residual	101	6374.13	63.11								
Total	102	6886.78									
a. Dependent Variable: Project Management Outcomes											
b. Predictors: (Constant), Costs of implementation											

*A function at the level of significance less than (0.05).

Table (36) presents the results of the simple linear regression analysis used to examine the effect of Costs of Implementation on Project Management Outcomes in design and consultancy engineering projects.

The results indicate that the correlation coefficient (R) equals (0.273), reflecting a relatively weak positive relationship between the costs of implementation and project management outcomes. The coefficient of determination ($R^2 = 0.074$) shows that 7.4% of the variation in project management outcomes can be explained by the costs of implementation, while the remaining variance is attributed to other factors not included in the model.

The F-test result ($F = 8.123$, $Sig = 0.005$) confirms that the regression model is statistically significant at the 0.05 level, indicating that the costs of implementation have a meaningful overall effect on project management outcomes.

Furthermore, the t-test result ($t = 2.850$, $Sig = 0.005$) reveals a positive and statistically significant relationship between costs of implementation and project management outcomes. The unstandardized regression coefficient ($B_1 = 1.28$) indicates that for every one-unit increase in implementation costs, project management outcomes improve by approximately (1.28) units.

These findings suggest that the costs associated with implementing AI technologies represent a significant factor influencing project management performance in design and consultancy engineering projects. Although higher implementation costs may initially represent a financial

challenge, they are often associated with enhanced technological infrastructure and improved project efficiency in the long term.

Hence, the results support the sub-hypothesis (H1C), which states that: “Costs of AI implementation have a statistically significant effect on project management outcomes in design and consultancy engineering projects.”

H1D: The compatibility of AI tools with existing infrastructure significantly influences project outcomes in design and consultancy engineering projects.

To test the main study Hypothesis H1D, the researcher used simple linear regression analysis of the effect of Compatibility with existing infrastructure on Project Management Outcomes in design and consultancy engineering projects.

Table (37) Test of Compatibility with existing infrastructure effect on Project Management Outcomes in design and consultancy engineering projects

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	1474.57	1474.57	0.463	0.214	37.15	2.75	27.518	0.000*	5.246	0.000*
Residual	101	5412.21	53.59								
Total	102	6886.78									
a. Dependent Variable: Project Management Outcomes											
b. Predictors: (Constant), Compatibility with existing infrastructure											

*A function at the level of significance less than (0.05).

Table (37) presents the results of the simple linear regression analysis conducted to examine the effect of Compatibility with Existing Infrastructure on Project Management Outcomes in design and consultancy engineering projects.

The results show that the correlation coefficient (R) equals (0.463), indicating a moderate to strong positive relationship between compatibility with existing infrastructure and project management outcomes. The coefficient of determination ($R^2 = 0.214$) reveals that 21.4% of the variance in project management outcomes can be explained by this variable, while the remaining variance is due to other factors not included in the model.

The F-test result ($F = 27.518$, $Sig = 0.000$) demonstrates that the regression model is statistically significant at a level below (0.05), suggesting that compatibility with existing infrastructure has a meaningful overall effect on project management outcomes.

Furthermore, the t-test result ($t = 5.246$, $Sig = 0.000$) indicates a positive and statistically significant effect of compatibility with existing infrastructure on project management outcomes. The unstandardized regression coefficient ($B_1 = 2.75$) implies that for every one-unit increase in compatibility, project management outcomes improve by approximately (2.75) units.

Accordingly, these findings suggest that compatibility with existing infrastructure is a key enabler of successful project management in design and consultancy engineering projects. It facilitates the integration of AI-based systems, enhances operational efficiency, and reduces organizational resistance to technological change.

Therefore, the results support the sub-hypothesis (H1D) which states that:

“Compatibility with existing infrastructure has a statistically significant effect on project management outcomes in design and consultancy engineering projects.”

H1E: The Workforce development significantly influences project outcomes in design and consultancy engineering projects.

To test the main study Hypothesis H1E, the researcher used simple linear regression analysis of the effect of Workforce Development on Project Management Outcomes in design and consultancy engineering projects.

Table (38) Test of Workforce Development effect on Project Management Outcomes in design and consultancy engineering projects

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	1679.40	1679.40	0.494	0.244	35.38	2.91	32.573	0.000*	5.707	0.000*
Residual	101	5207.38	51.56								
Total	102	6886.78									
a. Dependent Variable: Project Management Outcomes											
b. Predictors: (Constant), Workforce Development											

*A function at the level of significance less than (0.05).

Table (38) presents the results of the simple linear regression analysis conducted to examine the effect of Workforce Development on Project Management Outcomes in design and consultancy engineering projects.

The results indicate that the correlation coefficient (R) equals (0.494), suggesting a relatively strong positive relationship between workforce development and project management outcomes. The coefficient of determination ($R^2 = 0.244$) shows that 24.4% of the variance in project management outcomes can be explained by workforce development, while the remaining variance is attributed to other variables not included in the model.

The F-test result ($F = 32.573$, $Sig = 0.000$) confirms that the regression model is statistically significant at a level below (0.05), indicating that workforce development has a meaningful overall impact on project management outcomes.

Furthermore, the t-test result ($t = 5.707$, $Sig = 0.000$) reveals a positive and statistically significant effect of workforce development on project management outcomes. The unstandardized regression coefficient ($B_1 = 2.91$) indicates that for every one-unit increase in workforce development, project management outcomes improve by approximately (2.91) units.

These findings suggest that workforce development plays a vital role in enhancing project management performance in design and consultancy engineering projects. Improving employees' technical, analytical, and managerial skills contributes to greater efficiency, accuracy, and overall project success.

Therefore, the results support the sub-hypothesis (H1E), which states that:

“Workforce development has a statistically significant effect on project management outcomes in design and consultancy engineering projects.”

H1F: Ethical considerations significantly influence project outcomes in design and consultancy engineering projects.

To test the main study Hypothesis H1F, the researcher used simple linear regression analysis of the effect of Ethical Consideration on Project Management Outcomes in design and consultancy engineering projects.

Table (39) Test of Ethical Consideration effect on Project Management Outcomes in design and consultancy engineering projects

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	680.52	680.52	0.314	0.099	41.95	1.97	11.075	0.001*	3.328	0.001*
Residual	101	6206.26	61.45								
Total	102	6886.78									
a. Dependent Variable: Project Management Outcomes											
b. Predictors: (Constant), Ethical Consideration											

*A function at the level of significance less than (0.05).

Table (39) presents the results of the simple linear regression analysis examining the effect of Ethical Considerations on Project Management Outcomes in design and consultancy engineering projects.

The results show that the correlation coefficient ($R = 0.314$) indicates a moderate positive relationship between ethical considerations and project management outcomes. The coefficient of determination ($R^2 = 0.099$) reveals that 9.9% of the variance in project management outcomes can be explained by ethical considerations, while the remaining variance is attributed to other unexamined factors.

The F-test result ($F = 11.075$, $Sig = 0.001$) is statistically significant at the level of ($p < 0.05$), indicating that the regression model as a whole is significant and that ethical considerations have a meaningful impact on project management outcomes.

Similarly, the t-test result ($t = 3.328$, $Sig = 0.001$) confirms the significance of this relationship, showing that ethical considerations exert a positive and statistically significant influence on project management outcomes. The unstandardized regression coefficient ($B_1 = 1.97$) implies

that for every one-unit increase in ethical considerations, project management outcomes are expected to increase by approximately 1.97 units.

Accordingly, it can be concluded that adherence to ethical standards plays a vital role in enhancing project management effectiveness within design and consultancy engineering projects, as it promotes trust, transparency, and accountability within project teams.

These findings support the sub-hypothesis (H1F), which states that:

“Ethical considerations have a statistically significant effect on project management outcomes in design and consultancy engineering projects.”

H2 Impact of Independent Variables on Mediating Variable “AI-Based Project Management”.

H2: The factors influencing project management significantly influence the utilization of AI-based project management practices in design and consultancy engineering projects.

To test the main study Hypothesis H2, the researcher used simple linear regression analysis of the effect of factors influencing project management on AI-based project management practices in design and consultancy engineering projects.

Table (40) Test of factors influencing project management effect on AI-based project management practices in design and consultancy engineering projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	1255.10	1255.10	0.502	0.252	15.54	0.54	33.976	0.000*	5.829	0.000*
Residual	101	3731.02	36.94								
Total	102	4986.12									
a. Dependent Variable: AI-based project management practices											
b. Predictors: (Constant), factors influencing project management											

*A function at the level of significance less than (0.05).

Table (40) presents the results of the simple linear regression analysis examining the effect of factors influencing project management on AI-based project management practices in design and consultancy engineering projects.

The results show that the correlation coefficient ($R = 0.502$) indicates a moderate positive relationship between the factors influencing project management and the utilization of AI-based project management practices. Moreover, the coefficient of determination ($R^2 = 0.252$) reveals that approximately 25.2% of the variance in AI-based project management practices can be explained by the factors influencing project management, while the remaining variance is attributed to other factors not included in the model.

The results of the F-test ($F = 33.976$, $Sig = 0.000$) indicate a statistically significant model at a significance level less than (0.05), confirming that the overall regression model is significant and that the influencing factors have a meaningful impact on AI-based project management practices.

Furthermore, the t-test result ($t = 5.829$, $Sig = 0.000$) confirms a statistically significant positive effect, as indicated by the unstandardized coefficient ($B_1 = 0.54$). This implies that for every one-unit increase in the factors influencing project management, the level of AI-based project management practices increases by 0.54 units.

Accordingly, it can be concluded that enhancing organizational, administrative, and technical factors influencing project management effectively contributes to the greater utilization of AI-based project management practices within design and consultancy engineering organizations. These results support the main hypothesis (H2), which states that: “The factors influencing project management significantly influence the utilization of AI-based project management practices in design and consultancy engineering projects.”

To test the main study Hypothesis H2, the researcher used **Multiple linear regression Analysis** of the effect of factors influencing project management on AI-based project management practices in design and consultancy engineering projects.

Table (41) Test of factors influencing project management effect on AI-based project management practices in design and consultancy engineering projects.

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	33.514	3.480		9.631	0.000	3.832	0.053	3.66	
	Data Privacy and Security	0.895	0.457	0.191	1.957	0.053				3.66%
2	(Constant)	27.992	3.821		7.327	0.000	6.580	0.002*	11.3	
	Data Privacy and Security	0.100	0.513	0.021	0.195	0.846				3.66%
	Resistance to Change	1.482	0.493	0.330	3.004	0.003				7.97%
3	(Constant)	26.787	3.900		6.868	0.000	5.072	0.003*	13.32	
	Data Privacy and Security	0.085	0.511	0.018	0.167	0.868				3.66%
	Resistance to Change	0.964	0.617	0.214	1.564	0.121				7.97%
	Cost of AI Implementation	0.695	0.500	0.175	1.390	0.168				1.69%
4	(Constant)	20.199	3.811		5.300	0.000	10.107	0.000*	29.21	
	Data Privacy and Security	-0.596	0.487	-0.127	-1.226	0.223				3.66%
	Resistance to Change	0.469	0.570	0.104	0.822	0.413				7.97%
	Cost of AI Implementation	0.271	0.463	0.068	0.586	0.559				1.69%

	Compatibility with Existing Infrastructure	2.508	0.535	0.497	4.689	0.000				15.88%
5	(Constant)	16.542	3.882		4.262	0.000	10.403	0.000*	34.91	
	Data Privacy and Security	-0.550	0.469	-0.118	-1.173	0.244				3.66%
	Resistance to Change	0.202	0.557	0.045	0.362	0.718				7.97%
	Cost of AI Implementation	0.182	0.447	0.046	0.406	0.685				1.69%
	Compatibility with Existing Infrastructure	1.696	0.586	0.336	2.895	0.005				15.88%
	Workforce Development	1.582	0.543	0.316	2.914	0.004				5.70%
6	(Constant)	15.406	4.328		3.560	0.001	8.672	0.000*	35.15	
	Data Privacy and Security	-0.605	0.479	-0.129	-1.262	0.210				3.66%
	Resistance to Change	0.249	0.564	0.055	0.441	0.660				7.97%
	Cost of AI Implementation	0.178	0.449	0.045	0.397	0.693				1.69%
	Compatibility with Existing Infrastructure	1.575	0.621	0.312	2.534	0.013				15.88%
	Workforce Development	1.521	0.554	0.304	2.748	0.007				5.70%
	Ethical Considerations	0.323	0.536	0.061	0.602	0.549				0.24%

a. Dependent Variable: AI-based project management practices

*A function at the level of significance less than (0.05).

Table (41) presents the results of the Multiple linear regression analysis conducted to examine the impact of factors influencing project management on the utilization of AI-based project management practices in design and consultancy engineering projects.

The first model, which included only the variable Data Privacy and Security, explains 3.66% of the variance in AI-based project management practices, with an insignificant relationship (Sig = 0.053). This indicates that data privacy and security alone do not have a statistically significant influence on AI utilization in project management.

In the second model, after adding Resistance to Change, the explanatory power increased to 11.3%, and this variable showed a significant positive effect ($\beta = 0.330$, Sig = 0.003). This result highlights the importance of overcoming organizational resistance to facilitate the utilization of AI-based management tools.

The fourth model revealed a notable improvement in explanatory power ($R^2 = 29.21\%$) after including Compatibility with Existing Infrastructure, which had the strongest and most significant impact ($\beta = 0.497$, Sig = 0.000). This finding emphasizes that the technological readiness and compatibility of existing infrastructure are crucial for effective AI integration within engineering project management.

Furthermore, the fifth model showed that adding Workforce Development increased the explanatory power to 34.91%, with a significant influence ($\beta = 0.316$, Sig = 0.004). This implies that employee training and skill enhancement play a key role in supporting the implementation of AI-based practices.

In the final model, although Ethical Considerations were included, the most influential predictors remained Compatibility with Existing Infrastructure and Workforce Development, both maintaining statistical significance (Sig = 0.013 and 0.007, respectively). Other factors, including data privacy, resistance to change, cost of implementation, and ethics, showed no significant direct effect.

Overall, these results confirm that technological compatibility and workforce development are the primary drivers of AI-based project management utilization, while other factors act as secondary or supporting influences.

These findings support the main Hypothesis H2, which states that: The factors influencing project management significantly influence the utilization of AI-based project management practices in design and consultancy projects.

H2A: Data privacy and security significantly influence the utilization of AI-based project management practices in design and consultancy projects.

To test the main study Hypothesis H2A, the researcher used simple linear regression analysis of the effect of Data privacy and security on AI-based project management practices in design and consultancy projects.

Table (42) Test of Data privacy and security effect on AI-based project management practices in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	182.25	182.25	0.191	0.037	33.51	0.90	3.832	0.053	1.957	0.053
Residual	101	4803.67	47.56								
Total	102	4986.12									
a. Dependent Variable: AI-Based Project Management											
b. Predictors: (Constant), Data privacy and security											

*A function at the level of significance less than (0.05).

Table (42) presents the results of a simple linear regression analysis examining the effect of data privacy and security on AI-based project management practices in design and consultancy engineering projects.

The findings indicate a weak positive relationship between the two variables, as shown by the correlation coefficient ($R = 0.191$). The coefficient of determination ($R^2 = 0.037$) reveals that data privacy and security explain only about 3.7% of the variance in AI-based project management practices.

Moreover, the regression analysis shows that the effect is not statistically significant, with $F = 3.832$ and $Sig = 0.053$, which is slightly above the 0.05 significance threshold. Similarly, the t-test value ($t = 1.957$, $Sig = 0.053$) confirms that the influence of data privacy and security on AI-based project management practices is statistically insignificant.

Therefore, it can be concluded that data privacy and security do not have a direct or significant impact on the utilization of AI-based project management practices in design and consultancy engineering projects. This may be due to the fact that such organizations already maintain acceptable standards of data protection, making this factor less critical in influencing AI utilization levels.

H2B: Resistance to change significantly influences the utilization of AI-based project management practices in design and consultancy projects.

To test the main study Hypothesis H2B, the researcher used simple linear regression analysis of the effect of Resistance to change on AI-based project management practices in design and consultancy projects.

Table (43) Test of Resistance to change effect on AI-based project management practices in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	578.19	578.19	0.341	0.116	28.36	1.53	13.248	0.000*	3.640	0.000*
Residual	101	4407.93	43.64								
Total	102	4986.12									
a. Dependent Variable: AI-Based Project Management											
b. Predictors: (Constant), Resistance to change											

*A function at the level of significance less than (0.05).

Table (43) presents the results of a simple linear regression analysis examining the effect of resistance to change on AI-based project management practices in design and consultancy engineering projects.

The findings indicate a moderate positive relationship between the two variables, with a correlation coefficient of $R = 0.341$, suggesting that higher levels of resistance to change are associated with lower levels of utilization of AI-based management practices. The coefficient of determination ($R^2 = 0.116$) shows that resistance to change explains approximately 11.6% of the variance in AI-based project management practices.

The results also demonstrate a highly significant statistical effect, as evidenced by $F = 13.248$ ($Sig = 0.000$) and $t = 3.640$ ($Sig = 0.000$), confirming the meaningful influence of resistance to change on AI utilization.

These findings imply that resistance to change constitutes a major barrier to the successful implementation of AI-based project management practices, as organizational or individual reluctance to embrace innovation limits the integration of intelligent systems into project workflows.

Therefore, overcoming resistance to change is considered a critical prerequisite for achieving effective AI-driven transformation in project management within design and consultancy engineering environments.

H2C: Costs of implementation significantly influence the utilization of AI-based project management practices in design and consultancy projects.

To test the main study Hypothesis H2C, the researcher used simple linear regression analysis of the effect of Costs of implementation on AI-based project management practices in design and consultancy projects.

Table (44) Test of the Costs of implementation effect on AI-based project management practices in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	525.15	525.15	0.325	0.105	30.32	1.29	11.890	0.001*	3.448	0.001*
Residual	101	4460.67	44.17								
Total	102	4986.12									
a. Dependent Variable: AI-Based Project Management											
b. Predictors: (Constant), Costs of implementation											

*A function at the level of significance less than (0.05).

Table (44) reveals the findings of a simple linear regression analysis examining the effect of costs of implementation on AI-based project management practices in design and consultancy projects.

The analysis shows a moderate positive relationship between the two variables, as indicated by the correlation coefficient ($R = 0.325$), suggesting that implementation costs have a measurable influence on the utilization of AI-driven management practices. The coefficient of determination ($R^2 = 0.105$) indicates that approximately 10.5% of the variance in AI-based project management practices can be explained by implementation costs.

Furthermore, the model demonstrates a statistically significant effect, with $F = 11.890$ ($Sig = 0.001$) and $t = 3.448$ ($Sig = 0.001$), confirming that implementation costs exert a significant influence on AI-based project management utilization.

These findings imply that high implementation costs may act as a financial constraint, limiting the ability of design and consultancy firms to effectively integrate AI technologies into their project management processes. Therefore, reducing or optimizing implementation costs is essential to facilitate broader utilization of AI-based project management systems within the engineering sector.

H2D: Compatibility with existing infrastructure significantly influences the utilization of AI-based project management practices in design and consultancy projects.

To test the main study Hypothesis H2D, the researcher used simple linear regression analysis of the effect of Compatibility with existing infrastructure on AI-based project management practices in design and consultancy projects.

Table (45) Test of Compatibility with existing infrastructure effect on AI-based project management practices in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	1352.63	1352.63	0.521	0.271	20.54	2.63	37.599	0.000*	6.132	0.000*
Residual	101	3633.49	35.98								
Total	102	4986.12									
a. Dependent Variable: AI-Based Project Management											
b. Predictors: (Constant), Compatibility with existing infrastructure											

*A function at the level of significance less than (0.05).

Table (45) illustrate the effect of compatibility with existing infrastructure on AI-based project management practices in design and consultancy projects.

The findings reveal a strong positive correlation between the two variables ($R = 0.521$), indicating that compatibility plays a substantial role in facilitating the integration of AI systems within project management frameworks. The coefficient of determination ($R^2 = 0.271$) shows that approximately 27.1% of the variance in AI-based project management practices can be explained by the degree of infrastructure compatibility.

Moreover, the regression model demonstrates high statistical significance, as evidenced by $F = 37.599$ ($Sig = 0.000$) and $t = 6.132$ ($Sig = 0.000$), confirming that compatibility with existing infrastructure has a significant and positive impact on the utilization of AI-based project management.

These findings suggest that organizations with well-developed and adaptable infrastructures are more capable of integrating AI tools effectively, thereby enhancing project efficiency, data flow, and decision-making accuracy. Hence, improving infrastructure readiness is a critical prerequisite for maximizing the benefits of AI-driven project management practices in the engineering consultancy sector.

H2E: The workforce development significantly influences the utilization of AI-based project management practices in design and consultancy projects.

To test the main study Hypothesis H2E, the researcher used simple linear regression analysis of the effect of Workforce Development on AI-based project management practices in design and consultancy projects.

Table (46) Test of Workforce Development effect on AI-based project management practices in design and consultancy projects.

Model	df			(R)	(R ²)	B	B1	F test	T test
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		Sum of Squares	Mean Square					F	Sig	T	Sig
Regression	1	1384.50	1384.50	0.527	0.278	19.95	2.64	38.826	0.000*	6.231	0.000*
Residual	101	3601.61	35.66								
Total	102	4986.12									
a. Dependent Variable: AI-Based Project Management											
b. Predictors: (Constant), Workforce Development											

*A function at the level of significance less than (0.05).

Table (46) demonstrate a strong positive relationship between workforce development and AI-based project management practices in design and consultancy engineering projects. The correlation coefficient ($R = 0.527$) indicates a substantial association between the two variables, while the coefficient of determination ($R^2 = 0.278$) reveals that 27.8% of the variance in AI-based project management practices can be explained by workforce development.

The regression model is statistically significant, as reflected by the values $F = 38.826$ ($Sig = 0.000$) and $t = 6.231$ ($Sig = 0.000$), confirming that workforce development has a significant and positive impact on the implementation of AI-based project management.

These results emphasize the critical role of workforce training, skills enhancement, and technical readiness in facilitating the utilization and effective utilization of AI technologies. Consequently, investing in human capital and continuous professional development emerges as a strategic necessity for improving AI integration and achieving successful project outcomes in engineering consultancy contexts.

H2F: Ethical considerations significantly influence the utilization of AI-based project management practices in design and consultancy projects.

To test the main study Hypothesis H2F, the researcher used simple linear regression analysis of the effect of Ethical Consideration on AI-based project management practices in design and consultancy projects.

Table (47) Test of Ethical Consideration effect on AI-based project management practices in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	558.61	558.61	0.335	0.112	25.95	1.79	12.743	0.001*	3.570	0.001*
Residual	101	4427.51	43.84								
Total	102	4986.12									
a. Dependent Variable: AI-Based Project Management											
b. Predictors: (Constant). Ethical Consideration											

*A function at the level of significance less than (0.05).

Table (47) indicates a positive and statistically significant relationship between ethical considerations and AI-based project management practices in design and consultancy engineering projects. The correlation coefficient ($R = 0.335$) suggests a moderate association, while the coefficient of determination ($R^2 = 0.112$) shows that 11.2% of the variation in AI-based project management practices can be explained by ethical considerations.

The regression model is significant, as evidenced by the values $F = 12.743$ ($\text{Sig} = 0.001$) and $t = 3.570$ ($\text{Sig} = 0.001$), confirming that ethical considerations exert a notable positive influence on the effectiveness of AI-based project management.

These findings underscore the importance of integrating ethical principles, such as transparency, fairness, and data integrity, into AI applications within project management. Adhering to ethical standards not only enhances stakeholder trust but also promotes responsible AI utilization, ensuring that technological advancement aligns with professional and societal values.

H3 Impact of Mediating Variable “AI-Based Project Management” on Project Outcomes.

H3: The utilization of AI-based project management practices significantly influences project outcomes in design and consultancy engineering projects.

To test the main study Hypothesis H3, the researcher used simple linear regression analysis of the effect of AI-based project management practices on Project Management Outcomes in design and consultancy engineering projects.

Table (48) Test of AI-based project management practices effect on Project Management Outcomes in design and consultancy engineering projects

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	4133.07	4133.07	0.775	0.600	21.08	0.91	151.592	0.000*	12.312	0.000*
Residual	101	2753.70	27.26								
Total	102	6886.78									
a. Dependent Variable: Project Management Outcomes											
b. Predictors: (Constant), AI-based project management practices											

*A function at the level of significance less than (0.05).

Table (48) demonstrate a strong and statistically significant relationship between AI-based project management practices and project management outcomes in design and consultancy engineering projects. The correlation coefficient ($R = 0.775$) indicates a high positive correlation, while the coefficient of determination ($R^2 = 0.600$) reveals that 60% of the variance in project management outcomes can be attributed to the effective implementation of AI-based project management practices.

The regression model is highly significant, as evidenced by $F = 151.592$ ($\text{Sig} = 0.000$) and $t = 12.312$ ($\text{Sig} = 0.000$), confirming the substantial predictive power of AI-based project management on enhancing project performance outcomes.

These findings highlight that the integration of artificial intelligence tools and techniques in project management processes contributes significantly to improving efficiency, decision-making accuracy, risk mitigation, and overall project success. Consequently, organizations that

effectively adopt AI-driven management systems are more likely to achieve superior performance outcomes compared to those relying on traditional methods.

To test the main study Hypothesis H3, the researcher used **Multiple linear regression** analysis of the effect of AI-based project management practices on Project Management Outcomes in design and consultancy engineering projects.

Table (49) Test of AI-based project management practices effect on Project Management Outcomes in design and consultancy engineering projects

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	30.068	3.894		7.721	0.000	51.728	0.000*	33.87%	
	Streamline processes e.g., scheduling, documentation	3.434	0.477	0.582	7.192	0.000				33.87%
2	(Constant)	29.609	3.518		8.417	0.000	43.660	0.000*	46.62%	
	Streamline processes e.g., scheduling, documentation	1.062	0.649	0.180	1.637	0.105				33.87%
	Resource allocation	2.476	0.507	0.538	4.886	0.000				12.75%
3	(Constant)	27.011	3.494		7.730	0.000	34.427	0.000*	51.06%	
	Streamline processes e.g., scheduling, documentation	0.910	0.627	0.154	1.452	0.150				33.87%
	Resource allocation	1.314	0.623	0.285	2.110	0.037				12.75%
	Tasks Prioritizing	1.625	0.542	0.344	2.998	0.003				4.44%
4	(Constant)	23.731	3.436		6.907	0.000	31.928	0.000*	56.58%	
	Streamline processes e.g., scheduling, documentation	0.327	0.616	0.055	0.532	0.596				33.87%
	Resource allocation	1.003	0.596	0.218	1.682	0.096				12.75%
	Tasks Prioritizing	1.173	0.529	0.249	2.219	0.029				4.44%
	Progress reporting	1.714	0.485	0.333	3.531	0.001				5.52%
5	(Constant)	20.923	3.286		6.368	0.000	32.410	0.000*	62.56%	
	Streamline processes e.g., scheduling, documentation	0.385	0.575	0.065	0.669	0.505				33.87%

	Resource allocation	0.287	0.586	0.062	0.490	0.625				12.75%
	Tasks Prioritizing	1.155	0.494	0.245	2.339	0.021				4.44%
	Progress reporting	0.725	0.518	0.141	1.399	0.165				5.52%
	Communication	2.005	0.510	0.396	3.934	0.000				5.97%

a. Dependent Variable: Project Management Outcomes

*A function at the level of significance less than (0.05).

Table (49) reveal that AI-based project management practices collectively exert a strong and significant influence on project management outcomes within design and consultancy engineering projects. The sequential regression models demonstrate a progressive improvement in explanatory power, as the coefficient of determination (R^2) increased from 33.87% in Model 1 to 62.56% in Model 5, indicating that the inclusion of additional AI-related practices substantially enhances the model's predictive capability.

Among the predictors, Communication ($\beta = 0.396$, $t = 3.934$, $\text{Sig} = 0.000$), Progress Reporting ($\beta = 0.333$, $t = 3.531$, $\text{Sig} = 0.001$), and Tasks Prioritizing ($\beta = 0.245$, $t = 2.339$, $\text{Sig} = 0.021$) emerged as the most influential factors significantly influencing project management outcomes. These findings suggest that effective communication channels, systematic reporting mechanisms, and prioritization of project tasks play a pivotal role in enhancing project efficiency, coordination, and decision-making.

Conversely, variables such as streamlining processes and resource allocation did not show significant effects in the final model, indicating that while they contribute conceptually, their impact may be indirect or mediated through other AI-driven mechanisms.

Overall, the final model confirms that the integration of AI-based tools—particularly those enhancing communication, reporting, and prioritization—substantially improves project management performance, leading to more efficient, transparent, and data-informed project outcomes.

H3A: The utilization of AI-based project management practices significantly improves decision-making in design and consultancy projects.

To test the main study Hypothesis H3A, the researcher used simple linear regression analysis of the effect of AI-based project management practices on Decision-Making in design and consultancy projects.

Table (50) Test of AI-based project management practices effect on Decision-Making in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R ²)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	137.37	137.37	0.716	0.513	1.35	0.17	106.242	0.000*	10.307	0.000*
Residual	101	130.59	1.29								
Total	102	267.96									

a. Dependent Variable: Decision-Making
b. Predictors: (Constant), AI-Based Project Management

*A function at the level of significance less than (0.05).

Table (50) indicate that AI-based project management practices have a strong and statistically significant effect on decision-making in design and consultancy engineering projects. The correlation coefficient ($R = 0.716$) and the coefficient of determination ($R^2 = 0.513$) reveal that approximately 51.3% of the variance in decision-making effectiveness can be explained by the implementation of AI-based project management practices.

Furthermore, both the F-test (106.242) and T-test (10.307) values are statistically significant at a level less than (0.05), confirming the model's explanatory power and the existence of a genuine relationship between the studied variables.

These findings suggest that the integration of AI-based project management practices effectively enhances managerial decision-making quality by enabling more accurate data analysis, improving risk forecasting, and optimizing resource allocation — all of which contribute to better overall project performance.

To test the main study Hypothesis H3A, the researcher used **Multiple linear regression** analysis of the effect of AI-based project management practices on decision-making in design and consultancy projects.

Table (51) Test of AI-based project management practices effect on decision-making in design and consultancy projects.

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	2.497	0.762		3.274	0.001	54.024	0.000*	34.85%	
	Streamline processes e.g., scheduling, documentation	0.687	0.093	0.590	7.350	0.000				34.85%
2	(Constant)	2.445	0.742		3.297	0.001	32.012	0.000*	39.03%	
	Streamline processes e.g., scheduling, documentation	0.419	0.137	0.360	3.062	0.003				34.85%
	Resource allocation	0.280	0.107	0.308	2.620	0.010				4.18%
3	(Constant)	1.982	0.746		2.656	0.009	24.549	0.000*	42.66%	
	Streamline processes e.g., scheduling, documentation	0.392	0.134	0.337	2.928	0.004				34.85%

	Resource allocation	0.073	0.133	0.080	0.548	0.585				4.18%
	Tasks Prioritizing	0.290	0.116	0.311	2.501	0.014				3.62%
4	(Constant)	1.195	0.721		1.657	0.101	25.316	0.000*	50.82%	
	Streamline processes e.g., scheduling, documentation	0.252	0.129	0.217	1.950	0.054				34.85%
	Resource allocation	-0.002	0.125	-0.002	-0.014	0.989				4.18%
	Tasks Prioritizing	0.181	0.111	0.195	1.632	0.106				3.62%
	Progress reporting	0.411	0.102	0.404	4.033	0.000				8.16%
	(Constant)	0.727	0.710		1.025	0.308				
5	Streamline processes e.g., scheduling, documentation	0.262	0.124	0.225	2.107	0.038	23.793	0.000*	55.09%	34.85%
	Resource allocation	-0.121	0.127	-0.133	-0.957	0.341				4.18%
	Tasks Prioritizing	0.178	0.107	0.191	1.670	0.098				3.62%
	Progress reporting	0.246	0.112	0.242	2.198	0.030				8.16%
	Communication	0.334	0.110	0.335	3.036	0.003				4.27%

a. Dependent Variable: Decision-Making

*A function at the level of significance less than (0.05).

The results of the regression analysis demonstrate that AI-based project management practices exert a positive and statistically significant impact on decision-making within design and consultancy projects. The model shows a progressive improvement in explanatory power, reaching an R² value of 55.09%, indicating that more than half of the variation in decision-making efficiency can be explained by AI-related practices.

Among the examined predictors, streamlining processes ($\beta = 0.225$, $p = 0.038$), progress reporting ($\beta = 0.242$, $p = 0.030$), and communication ($\beta = 0.335$, $p = 0.003$) emerged as the most influential factors contributing to enhanced decision-making. These findings underscore the role of AI tools in improving process automation, promoting transparency through accurate progress tracking, and strengthening coordination among stakeholders, which collectively lead to more informed and timely project decisions.

H3B: The utilization of AI-based project management practices significantly improves project quality in design and consultancy projects.

To test the main study Hypothesis H3B, the researcher used simple linear regression analysis of the effect of AI-based project management practices on Project Quality in design and consultancy projects.

Table (52) Test of AI-based project management practices effect on Project Quality in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	114.59	114.59	0.675	0.456	2.06	0.15	84.529	0.000*	9.194	0.000*
Residual	101	136.92	1.36								
Total	102	251.52									
a. Dependent Variable: Project Quality											
b. Predictors: (Constant), AI-Based Project Management											

*A function at the level of significance less than (0.05).

The results indicate that AI-based project management practices have a positive and statistically significant effect on project quality in design and consultancy projects. The correlation coefficient ($R = 0.675$) and the coefficient of determination ($R^2 = 0.456$) suggest that approximately 45.6% of the variance in project quality can be explained by the implementation of AI-based project management practices.

The regression model is highly significant, as indicated by $F = 84.529$ ($\text{Sig} = 0.000$) and $t = 9.194$ ($\text{Sig} = 0.000$), confirming the strength of the relationship between AI-based project management and project quality.

These findings highlight the pivotal role of AI in enhancing operational efficiency, monitoring performance, and ensuring adherence to engineering and quality standards, ultimately contributing to more accurate, reliable, and effective project outcomes.

To test the main study Hypothesis H3B, the researcher used **Multiple linear regression** analysis of the effect of AI-based project management practices on project quality in design and consultancy projects.

Table (53) Test of AI-based project management practices effect on project quality in design and consultancy projects.

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	3.508	0.786		4.465	0.000	36.025	0.000*	26.29%	
	Streamline processes e.g., scheduling, documentation	0.578	0.096	0.513	6.002	0.000				26.29%
2	(Constant)	3.435	0.741		4.634	0.000	27.045	0.000*	35.10%	
	Streamline processes e.g.,	0.201	0.137	0.179	1.472	0.144				26.29%

	scheduling, documentation									
	Resource allocation	0.393	0.107	0.447	3.685	0.000				8.81%
3	(Constant)	3.148	0.760		4.141	0.000	19.043	0.000*	36.59%	
	Streamline processes e.g., scheduling, documentation	0.184	0.136	0.164	1.353	0.179				26.29%
	Resource allocation	0.265	0.136	0.301	1.955	0.053				8.81%
	Tasks Prioritizing	0.180	0.118	0.199	1.524	0.131				1.49%
4	(Constant)	2.343	0.734		3.190	0.002	20.617	0.000*	45.70%	
	Streamline processes e.g., scheduling, documentation	0.042	0.132	0.037	0.315	0.753				26.29%
	Resource allocation	0.189	0.127	0.214	1.480	0.142				8.81%
	Tasks Prioritizing	0.069	0.113	0.076	0.609	0.544				1.49%
	Progress reporting	0.420	0.104	0.427	4.054	0.000				9.11%
5	(Constant)	2.005	0.740		2.712	0.008	17.952	0.000*	48.06%	
	Streamline processes e.g., scheduling, documentation	0.048	0.129	0.043	0.374	0.709				26.29%
	Resource allocation	0.103	0.132	0.116	0.778	0.439				8.81%
	Tasks Prioritizing	0.067	0.111	0.074	0.600	0.550				1.49%
	Progress reporting	0.302	0.117	0.306	2.586	0.011				9.11%
	Communication	0.241	0.115	0.249	2.101	0.038				2.36%

a. Dependent Variable: Project Quality

*A function at the level of significance less than (0.05).

The regression analysis demonstrates that AI-based project management practices have a positive and statistically significant effect on project quality in design and consultancy projects. The model shows a progressive increase in explanatory power, with the final model explaining 48.06% of the variance in project quality ($R^2 = 0.4806$).

Among the specific practices, progress reporting ($\beta = 0.306$, $p = 0.011$) and communication ($\beta = 0.249$, $p = 0.038$) emerged as the most significant predictors of project quality, indicating that timely reporting and effective stakeholder communication are critical in achieving higher quality outcomes. Resource allocation also showed a notable contribution in earlier models, highlighting the importance of efficiently distributing resources to enhance project performance.

These results underline the pivotal role of AI in optimizing project workflows, monitoring progress, and facilitating effective communication, all of which contribute to improved quality, reliability, and overall project success.

H3C: The utilization of AI-based project management practices significantly improves data collection accuracy in design and consultancy projects.

To test the main study Hypothesis H3C, the researcher used simple linear regression analysis of the effect of AI-based project management practices on Data Collection Accuracy in design and consultancy projects.

Table (54) Test of AI-based project management practices effect on Data Collection Accuracy in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	69.11	69.11	0.566	0.321	3.62	0.12	47.706	0.000*	6.907	0.000*
Residual	101	146.31	1.45								
Total	102	215.42									
a. Dependent Variable: Data Collection Accuracy											
b. Predictors: (Constant), AI-Based Project Management											

*A function at the level of significance less than (0.05).

The results indicate that AI-based project management practices have a positive and statistically significant impact on data collection accuracy in design and consultancy projects. The correlation coefficient ($R = 0.566$) and the coefficient of determination ($R^2 = 0.321$) suggest that approximately 32.1% of the variance in data collection accuracy can be explained by the application of AI-based project management practices.

The regression model is highly significant, as indicated by $F = 47.706$ ($Sig = 0.000$) and $t = 6.907$ ($Sig = 0.000$), confirming the strength and reliability of the relationship between AI-based project management and improved data accuracy.

These findings highlight the role of AI in enhancing precision during data collection, reducing human errors, and enabling more reliable and accurate information gathering, which are essential for effective project monitoring and decision-making.

To test the main study Hypothesis H3C, the researcher used **Multiple linear regression** analysis of the effect of AI-based project management practices on data collection accuracy in design and consultancy projects.

Table (55) Test of AI-based project management practices effect on data collection accuracy in design and consultancy projects.

Coefficient ^a								
Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.	F	Sig.	R square	

		B	Std. Error	Beta						R square change
1	(Constant)	5.074	0.780		6.508	0.000	18.165	0.000*	15.24%	
	Streamline processes e.g., scheduling, documentation	0.407	0.096	0.390	4.262	0.000				15.24%
2	(Constant)	5.016	0.753		6.662	0.000	13.948	0.000*	21.81%	
	Streamline processes e.g., scheduling, documentation	0.106	0.139	0.102	0.765	0.446				15.24%
	Resource allocation	0.314	0.108	0.386	2.898	0.005				6.57%
3	(Constant)	4.721	0.772		6.116	0.000	10.221	0.000*	23.65%	
	Streamline processes e.g., scheduling, documentation	0.089	0.138	0.085	0.643	0.522				15.24%
	Resource allocation	0.182	0.138	0.224	1.324	0.188				6.57%
	Tasks Prioritizing	0.185	0.120	0.221	1.543	0.126				1.84%
4	(Constant)	3.759	0.721		5.212	0.000	15.557	0.000*	38.84%	
	Streamline processes e.g., scheduling, documentation	-0.082	0.129	-0.078	-0.633	0.528				15.24%
	Resource allocation	0.091	0.125	0.112	0.727	0.469				6.57%
	Tasks Prioritizing	0.052	0.111	0.063	0.471	0.638				1.84%
	Progress reporting	0.503	0.102	0.552	4.933	0.000				15.19%
5	(Constant)	3.644	0.741		4.919	0.000	12.485	0.000*	39.16%	
	Streamline processes e.g., scheduling, documentation	-0.079	0.130	-0.076	-0.613	0.541				15.24%
	Resource allocation	0.062	0.132	0.076	0.467	0.641				6.57%
	Tasks Prioritizing	0.052	0.111	0.062	0.463	0.644				1.84%
	Progress reporting	0.462	0.117	0.507	3.956	0.000				15.19%
	Communication	0.082	0.115	0.092	0.714	0.477				0.32%

a. Dependent Variable: Data Collection Accuracy

*A function at the level of significance less than (0.05).

The hierarchical regression analysis demonstrates that AI-based project management practices significantly enhance data collection accuracy in design and consultancy projects. The final model

explains 39.16% of the variance in data collection accuracy ($R^2 = 0.3916$), indicating a substantial impact of AI-enabled project management on improving the reliability of collected data.

Among the specific AI-based practices, progress reporting emerged as the most significant predictor ($\beta = 0.507$, $p = 0.000$), highlighting the role of systematic monitoring and timely reporting in ensuring accurate data collection. While other practices such as resource allocation and communication showed smaller or non-significant effects in the final model, they contributed to the overall explanatory power in earlier steps.

These results underscore the importance of AI-based tools in streamlining project workflows, enhancing monitoring, and reducing human error, thereby supporting more accurate and reliable data collection, which is critical for informed decision-making and project performance.

H3D: The utilization of AI-based project management practices significantly improves data analysis and insight generation in design and consultancy projects.

To test the main study Hypothesis H3D, the researcher used **simple linear regression** analysis of the effect of AI-based project management practices on Data Analysis and insight generation in design and consultancy projects.

Table (56) Test of AI-based project management practices effect on Data Analysis and insight generation in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	46.72	46.72	0.495	0.245	4.53	0.10	32.694	0.000*	5.718	0.000*
Residual	101	144.33	1.43								
Total	102	191.05									
a. Dependent Variable: Data Analysis and insight generation											
b. Predictors: (Constant), AI-Based Project Management											

*A function at the level of significance less than (0.05).

The results indicate that AI-based project management practices have a positive and statistically significant effect on data analysis and insight generation in design and consultancy projects. The correlation coefficient ($R = 0.495$) and coefficient of determination ($R^2 = 0.245$) suggest that approximately 24.5% of the variance in data analysis and insight generation can be explained by the application of AI-based project management practices.

The regression model is highly significant, as indicated by $F = 32.694$ ($\text{Sig} = 0.000$) and $t = 5.718$ ($\text{Sig} = 0.000$), confirming the reliability and strength of the relationship between AI-based project management and improved analytical outcomes.

These findings highlight the crucial role of AI in enhancing the processing and interpretation of project data, enabling more accurate insights, and supporting evidence-based decision-making in design and consultancy projects.

To test the main study Hypothesis H3D, the researcher used **Multiple linear regression** analysis of the effect of AI-based project management practices on data analysis and insight generation in design and consultancy projects.

Table (57) Test of AI-based project management practices effect on data analysis and insight generation in design and consultancy projects.

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	5.316	0.734		7.247	0.000	18.406	0.000*	15.41%	
	Streamline processes e.g., scheduling, documentation	0.386	0.090	0.393	4.290	0.000				15.41%
2	(Constant)	5.275	0.721		7.315	0.000	11.834	0.000*	19.14%	
	Streamline processes e.g., scheduling, documentation	0.172	0.133	0.175	1.295	0.198				15.41%
	Resource allocation	0.223	0.104	0.291	2.146	0.034				3.72%
3	(Constant)	4.817	0.725		6.646	0.000	10.483	0.000*	24.11%	
	Streamline processes e.g., scheduling, documentation	0.145	0.130	0.148	1.119	0.266				15.41%
	Resource allocation	0.018	0.129	0.024	0.141	0.888				3.72%
	Tasks Prioritizing	0.286	0.112	0.364	2.546	0.012				4.97%
4	(Constant)	4.645	0.754		6.162	0.000	8.017	0.000*	24.65%	
	Streamline processes e.g., scheduling, documentation	0.115	0.135	0.117	0.851	0.397				15.41%
	Resource allocation	0.002	0.131	0.002	0.015	0.988				3.72%
	Tasks Prioritizing	0.263	0.116	0.334	2.263	0.026				4.97%
	Progress reporting	0.090	0.106	0.105	0.843	0.401				0.55%
5	(Constant)	4.378	0.766		5.714	0.000	7.029	0.000*	26.60%	
	Streamline processes e.g., scheduling, documentation	0.120	0.134	0.123	0.898	0.371				15.41%
	Resource allocation	-0.066	0.137	-0.086	-0.484	0.629				3.72%

	Tasks Prioritizing	0.261	0.115	0.332	2.266	0.026				4.97%
	Progress reporting	-0.004	0.121	-0.005	-0.034	0.973				0.55%
	Communication	0.190	0.119	0.226	1.602	0.112				1.94%

a. Dependent Variable: Data Analysis and insight generation

*A function at the level of significance less than (0.05).

The results indicate that AI-based project management practices have a positive and statistically significant impact on data analysis and insight generation in design and consultancy projects. The final regression model shows that approximately 26.6% of the variance in data analysis and insight generation ($R^2 = 0.266$) is explained by the implementation of AI-based project management practices, highlighting their substantial role in enhancing analytical quality.

Among the practices, Tasks Prioritizing emerged as the most influential factor ($\beta \approx 0.332$ – 0.364 , $p < 0.05$) in improving the team's ability to extract accurate insights from project data. Other practices, such as Resource Allocation, Communication, and Progress Reporting, showed varying effects, some of which were not statistically significant in the final model, though they contributed partially to the model's explanatory power.

These findings emphasize the critical role of AI in enhancing data organization, supporting evidence-based decision-making, and improving analytical efficiency in design and consultancy projects.

H3E: The utilization of AI-based project management practices significantly improves risk identification and mitigation in design and consultancy projects.

To test the main study Hypothesis H3E, the researcher used **simple linear regression** analysis of the effect of AI-based project management practices on Risk Identification Accuracy in design and consultancy projects.

Table (58) Test of AI-based project management practices effect on Risk Identification Accuracy in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	113.89	113.89	0.677	0.459	2.20	0.15	85.521	0.000*	9.248	0.000*
Residual	101	134.50	1.33								
Total	102	248.39									
a. Dependent Variable: Risk Identification Accuracy											
b. Predictors: (Constant), AI-Based Project Management											

*A function at the level of significance less than (0.05).

The results demonstrate that AI-based project management practices have a significant positive impact on risk identification accuracy in design and consultancy projects. The model indicates

that approximately 45.9% of the variance in risk identification accuracy ($R^2 = 0.459$) can be explained by the utilization of AI-based practices, highlighting their substantial contribution to improving project risk management processes.

The high F-value ($F = 85.521$, $p < 0.001$) and significant t-value ($t = 9.248$, $p < 0.001$) confirm the robustness of the model, indicating that AI-based project management practices effectively enhance the precision and reliability of risk identification, enabling project teams to anticipate, evaluate, and mitigate potential risks more efficiently.

This underscores the critical role of AI tools in strengthening risk management capabilities, supporting proactive decision-making, and improving overall project performance.

To test the main study Hypothesis H3E, the researcher used **Multiple linear regression** analysis of the effect of AI-based project management practices on risk identification and mitigation in design and consultancy projects.

Table (59) Test of AI-based project management practices effect on risk identification and mitigation in design and consultancy projects.

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	3.765	0.787		4.781	0.000	33.725	0.000*	25.03%	
	Streamline processes e.g., scheduling, documentation	0.561	0.097	0.500	5.807	0.000				25.03%
2	(Constant)	3.679	0.722		5.096	0.000	30.224	0.000*	37.67%	
	Streamline processes e.g., scheduling, documentation	0.112	0.133	0.100	0.842	0.402				25.03%
	Resource allocation	0.468	0.104	0.535	4.504	0.000				12.64%
3	(Constant)	3.182	0.721		4.411	0.000	24.065	0.000*	42.17%	
	Streamline processes e.g., scheduling, documentation	0.083	0.129	0.074	0.641	0.523				25.03%
	Resource allocation	0.246	0.129	0.282	1.915	0.058				12.64%
	Tasks Prioritizing	0.311	0.112	0.346	2.775	0.007				4.50%
4	(Constant)	2.742	0.735		3.731	0.000	19.988	0.000*	44.93%	
	Streamline processes e.g., scheduling, documentation	0.005	0.132	0.004	0.036	0.971				25.03%

5	Resource allocation	0.205	0.128	0.234	1.604	0.112	17.345	0.000*	47.20%	12.64%
	Tasks Prioritizing	0.250	0.113	0.279	2.209	0.030				4.50%
	Progress reporting	0.230	0.104	0.235	2.215	0.029				2.76%
	(Constant)	2.413	0.741		3.256	0.002				
	Streamline processes e.g., scheduling, documentation	0.012	0.130	0.010	0.089	0.929				25.03%
	Resource allocation	0.121	0.132	0.138	0.913	0.363				12.64%
	Tasks Prioritizing	0.248	0.111	0.276	2.225	0.028				4.50%
	Progress reporting	0.114	0.117	0.117	0.976	0.331				2.76%
	Communication	0.235	0.115	0.245	2.045	0.044				2.28%

a. Dependent Variable: Risk Identification Accuracy

*A function at the level of significance less than (0.05).

The results of the table indicate that AI-based project management practices have a positive and statistically significant effect on risk identification and mitigation in design and consultancy projects. The model shows that approximately 47.2% of the variance in risk identification and mitigation effectiveness can be explained by the utilization of these practices ($R^2 = 0.472$), highlighting their critical role in enhancing project risk management.

Additionally, the high F-value ($F = 17.345$, $p < 0.001$) and significant t-values for the model components confirm that scheduling, resource allocation, task prioritization, progress reporting, and communication play key roles in improving the accuracy of risk identification and the effectiveness of mitigation measures.

Overall, the findings suggest that leveraging AI tools strengthens project teams' ability to anticipate risks and take proactive actions, thereby reducing the likelihood of issues and improving project quality and operational efficiency.

H3F: The utilization of AI-based project management practices significantly reduces time spent by project managers on routine tasks in design and consultancy projects.

To test the main study Hypothesis H3F, the researcher used **simple linear regression** analysis of the effect of AI-based project management practices on reduces time spent by Project Managers in design and consultancy projects.

Table (60) Test of AI-based project management practices effect on reducing time spent by Project Managers in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	38.14	38.14								

Residual	101	119.61	1.18	0.492	0.242	4.98	0.09	32.209	0.000*	5.675	0.000*
Total	102	157.75									
a. Dependent Variable: reduces time spent by Project Managers											
b. Predictors: (Constant), AI-Based Project Management											

*A function at the level of significance less than (0.05).

The results indicate that AI-based project management practices have a significant and positive impact on reducing the time spent by project managers in design and consultancy projects. The model explains approximately 24.2% of the variance in time efficiency ($R^2 = 0.242$), demonstrating that adopting AI tools contributes meaningfully to optimizing project management processes.

The high F-value ($F = 32.209$, $p < 0.001$) confirms the overall model significance, while the significant t-value ($t = 5.675$, $p < 0.001$) indicates that AI-based practices, such as streamlining scheduling, documentation, and resource allocation, effectively reduce managerial workload.

These findings suggest that implementing AI tools enhances operational efficiency, allowing project managers to allocate their time more strategically to critical tasks, thereby improving project performance and productivity.

To test the main study Hypothesis H3F, the researcher used **Multiple linear regression** analysis of the effect of AI-based project management practices on reduces time spent by Project Managers in design and consultancy projects.

Table (61) Test of AI-based project management practices effect on reduces time spent by Project Managers in design and consultancy projects.

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	6.016	0.680		8.844	0.000	13.682	0.000*	11.93%	
	Streamline processes e.g., scheduling, documentation	0.308	0.083	0.345	3.699	0.000				11.93%
2	(Constant)	5.957	0.647		9.204	0.000	13.371	0.000*	21.10%	
	Streamline processes e.g., scheduling, documentation	0.004	0.119	0.004	0.034	0.973				11.93%
	Resource allocation	0.318	0.093	0.456	3.409	0.001				9.17%
3	(Constant)	5.633	0.659		8.554	0.000	10.483	0.000*	24.11%	
	Streamline processes e.g., scheduling, documentation	-0.015	0.118	-0.017	-0.127	0.899				11.93%

	Resource allocation	0.173	0.117	0.248	1.475	0.143				9.17%
	Tasks Prioritizing	0.202	0.102	0.283	1.981	0.050				3.01%
4	(Constant)	5.697	0.687		8.291	0.000	7.821	0.000*	24.20%	
	Streamline processes e.g., scheduling, documentation	-0.004	0.123	-0.004	-0.030	0.976				11.93%
	Resource allocation	0.179	0.119	0.257	1.503	0.136				9.17%
	Tasks Prioritizing	0.211	0.106	0.295	1.996	0.049				3.01%
	Progress reporting	-0.033	0.097	-0.043	-0.342	0.733				0.09%
	(Constant)	5.179	0.665		7.790	0.000				
5	Streamline processes e.g., scheduling, documentation	0.007	0.116	0.008	0.059	0.953	9.584	0.000*	33.07%	11.93%
	Resource allocation	0.047	0.118	0.068	0.398	0.692				9.17%
	Tasks Prioritizing	0.208	0.100	0.291	2.079	0.040				3.01%
	Progress reporting	-0.216	0.105	-0.276	-2.056	0.042				0.09%
	Communication	0.370	0.103	0.483	3.585	0.001				8.87%
	(Constant)	5.179	0.665		7.790	0.000				

a. Dependent Variable: reduces time spent by Project Managers

*A function at the level of significance less than (0.05).

The results indicate that AI-based project management practices significantly influence the reduction of time spent by project managers in design and consultancy projects. The regression analysis shows a progressive increase in the explanatory power of the model across steps, with the final model accounting for approximately 33.07% of the variance in time efficiency ($R^2 = 0.3307$). From the coefficients analysis:

- Streamlining processes (e.g., scheduling, documentation) initially shows a significant positive effect ($\beta = 0.345$, $p < 0.001$), highlighting its role in improving time efficiency. However, its impact diminishes in the later models when combined with other variables.
- Resource allocation shows a strong positive effect in early models ($\beta = 0.456$, $p = 0.001$), indicating that optimizing resource assignment is a key factor in reducing managerial time.
- Tasks prioritizing and communication emerge as significant contributors in the final model ($\beta = 0.291$, $p = 0.040$; $\beta = 0.483$, $p = 0.001$), suggesting that focusing on critical tasks and enhancing communication further improves time efficiency.
- Progress reporting shows a negative coefficient in the final model ($\beta = -0.276$, $p = 0.042$), which may indicate that extensive reporting, if not optimized, could slightly offset time-saving benefits.

- Overall, the findings demonstrate that a comprehensive utilization of AI-based practices, combining process automation, effective resource allocation, task prioritization, and communication, significantly reduces the time spent by project managers, thus enhancing overall project efficiency and productivity.

H3G: The utilization of AI-based project management practices significantly improves communication among stakeholders in design and consultancy projects.

To test the main study Hypothesis H3G, the researcher used simple linear regression analysis of the effect of AI-based project management practices on communication among stakeholders in design and consultancy projects.

Table (62) Test of AI-based project management practices effect on communication among stakeholders in design and consultancy projects (Simple linear regression based).

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	97.37	97.37	0.629	0.369	2.34	0.14	66.236	0.000*	8.139	0.000*
Residual	101	148.48	1.47								
Total	102	245.85									
a. Dependent Variable: communication among stakeholders											
b. Predictors: (Constant), AI-Based Project Management											

*A function at the level of significance less than (0.05).

The results demonstrate that AI-based project management practices have a significant positive effect on communication among stakeholders in design and consultancy projects. The regression model shows that the predictor variable explains approximately 36.9% of the variance in stakeholder communication ($R^2 = 0.369$), indicating a substantial influence.

The high F-value ($F = 66.236$, $p < 0.001$) confirms the overall significance of the model, while the t-test for the predictor ($t = 8.139$, $p < 0.001$) further emphasizes that AI-based practices are a strong and statistically significant factor in enhancing communication.

These findings suggest that the implementation of AI-based project management tools and practices, such as automated scheduling, progress tracking, and centralized information sharing, can streamline interactions, improve clarity, and facilitate timely information exchange among stakeholders, thereby promoting collaboration and reducing misunderstandings in project execution.

To test the main study Hypothesis H3G, the researcher used **Multiple linear regression** analysis of the effect of AI-based project management practices on communication among stakeholders in design and consultancy projects.

Table (63) Test of AI-based project management practices effect on communication among stakeholders in design and consultancy projects (Multiple linear regression based).

Coefficient ^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	3.892	0.806		4.828	0.000	26.242	0.000*	20.62%	
	Streamline processes e.g., scheduling, documentation	0.506	0.099	0.454	5.123	0.000				20.62%
2	(Constant)	3.803	0.739		5.146	0.000	25.760	0.000*	34.00%	
	Streamline processes e.g., scheduling, documentation	0.047	0.136	0.042	0.346	0.730				20.62%
	Resource allocation	0.479	0.106	0.551	4.502	0.000				13.38%
3	(Constant)	3.528	0.759		4.651	0.000	18.079	0.000*	35.39%	
	Streamline processes e.g., scheduling, documentation	0.031	0.136	0.028	0.228	0.820				20.62%
	Resource allocation	0.356	0.135	0.410	2.636	0.010				13.38%
	Tasks Prioritizing	0.172	0.118	0.193	1.461	0.147				1.39%
4	(Constant)	3.350	0.789		4.245	0.000	13.693	0.000*	35.85%	
	Streamline processes e.g., scheduling, documentation	-0.001	0.141	-0.001	-0.004	0.997				20.62%
	Resource allocation	0.339	0.137	0.390	2.479	0.015				13.38%
	Tasks Prioritizing	0.147	0.121	0.165	1.213	0.228				1.39%
	Progress reporting	0.093	0.111	0.096	0.837	0.405				0.46%
5	(Constant)	2.576	0.728		3.540	0.001	18.312	0.000*	48.56%	
	Streamline processes e.g., scheduling, documentation	0.015	0.127	0.014	0.119	0.905				20.62%
	Resource allocation	0.142	0.130	0.163	1.096	0.276				13.38%
	Tasks Prioritizing	0.142	0.109	0.159	1.300	0.197				1.39%
	Progress reporting	-0.179	0.115	-0.184	-1.562	0.122				0.46%
	Communication	0.553	0.113	0.578	4.894	0.000				12.70%

a. Dependent Variable: communication among stakeholders

*A function at the level of significance less than (0.05).

The results of the regression analysis indicate that AI-based project management practices significantly influence communication among stakeholders in design and consultancy projects.

The final model (Model 5) explains approximately 48.56% of the variance in stakeholder communication ($R^2 = 0.4856$), highlighting a strong overall effect.

Among the components of AI-based practices, communication tools demonstrate the strongest and most statistically significant impact ($B = 0.553$, $\beta = 0.578$, $t = 4.894$, $p < 0.001$), indicating that the use of AI-driven communication mechanisms substantially improves information exchange among project stakeholders. Other factors, such as resource allocation, progress reporting, and task prioritization, contribute to a lesser extent and are mostly not statistically significant in the final model.

H1 INTERPRETATION SUMMAR

Hypothesis H1 proposed that some of the organizational and technical factors identified through the literature review and the researcher's professional experience — recognizing that other influencing conditions may exist beyond those examined in this study — influence project outcomes.

Table 64 presents the simple linear regression results for the overall H1 model and its six sub-hypotheses. The overall model was statistically significant, explaining 23.5% of the variance in project outcomes ($R = 0.485$, $R^2 = 0.235$, $F = 30.989$, $p < .001$). Therefore, H1 was supported in the simple regression analysis.

Statistical Evidence:

- Correlation coefficient: $R = 0.485$ (moderate positive relationship)
- Coefficient of determination: $R^2 = 0.235$ (factors explain 23.5% of variance)
- F-test: $F = 30.989$, $p = 0.000$ (highly significant)
- t-test: $t = 5.567$, $p = 0.000$ (highly significant)
- Regression coefficient: $B_1 = 0.61$ (one-unit increase in factors $\rightarrow$ 0.61 unit increase in outcomes)

Key Insight:

All six factors were individually significant predictors of project outcomes in the simple regression analyses, together explaining 23.5% of the variance in the overall simple-regression model. However, the stepwise multiple-regression analysis revealed a more selective pattern: workforce development was the only factor to retain statistical significance in the final model ($B = 1.819$, $p = .009$). Infrastructure compatibility was a significant predictor when first introduced at an earlier step of the model ($p = .001$) but lost significance once workforce development and ethical considerations were added (final model $p = .123$), indicating that its apparent influence substantially overlapped with workforce development's effect. This pattern

is consistent with Bodea et al. (2020) and Müller et al. (2024), who similarly found that technical readiness functions as a necessary but not independently sufficient condition, with workforce capability serving as the more proximate determinant of measurable project outcomes.

Table (65) ranks these factors by their regression coefficients (B_1), providing a clear comparison of their relative impact on project management outcomes. This ranking reveals which organizational factors exert the strongest influence on project success.

Table (65) Sub-Hypothesis Result (H1A-H1F) with Ranking by Effect Size

SUB-HYPOTHESIS RESULTS (H1A-H1F):						
Rank	Hypothesis	Variable	B_1 Coefficient	Effect Magnitude	p- value	Interpretation
1	H1E	Workforce Development	2.91	STRONGEST	0	Every 1-unit increase in workforce development increases outcomes by 2.91 units
2	H1D	Infrastructure Compatibility	2.75	VERY STRONG	0	Every 1-unit increase in infrastructure compatibility increases outcomes by 2.75 units
3	H1F	Ethical Considerations	1.97	STRONG	0.001	Every 1-unit increase in ethics increases outcomes by 1.97 units
4	H1B	Resistance to Change	1.82	STRONG	0	Every 1-unit increase in managing resistance increases outcomes by 1.82 units
5	H1A	Data Privacy & Security	1.52	MODERATE-STRONG	0.005	Every 1-unit increase in privacy/security increases outcomes by 1.52 units
6	H1C	Cost of AI Implementation	1.28	MODERATE	0.005	Every 1-unit increase in cost increases outcomes by 1.28 units

Key Findings & Interpretation:

Workforce development ($B=2.91$) had the largest unstandardized coefficient in the individual simple-regression results, followed by infrastructure compatibility ($B=2.75$). These coefficients describe the estimated associations in the separate models and should not be interpreted as unique effects after controlling for all other predictors. In the combined multiple-regression model, infrastructure compatibility ($B=2.278, p=.001$, $B=2.278, p=.001$) and workforce development ($B=1.880, p=.006$, $B=1.880, p=.006$) remained statistically significant.

The H1 results establish direct associations between the influencing factors and project outcomes. The next hypothesis group examines whether these factors also predict AI-based project-management utilization. The mediation analysis later tests whether AI-based project

management serves as the mechanism through which the influencing factors affect project outcomes.

H2 INTERPRETATION SUMMARY

Hypothesis H2 examined whether the six organizational and technical factors influence the utilization of AI-based project-management practices. Table 66 presents the simple linear regression results for the overall H2 model and its six sub-hypotheses.

The overall H2 model was statistically significant and explained 25.2% of the variance in AI-based project-management utilization ($R = 0.502$, $R^2 = 0.252$, $F = 33.976$, $p < .001$). Therefore, the main H2 hypothesis was supported in the simple regression analysis.

Statistical evidence

- Correlation coefficient: $R = 0.502$, indicating a moderate positive relationship.
- Coefficient of determination: $R^2 = 0.252$, indicating that the factors explained 25.2% of the variance in AI-based project-management utilization.
- F -test: $F = 33.976$, $p < .001$, indicating that the overall model was statistically significant.
- t -test: $t = 5.829$, $p < .001$, indicating a statistically significant overall effect.
- Regression coefficient: $B_1 = 0.54$.

The individual simple-regression results showed that resistance to change, cost of AI implementation, infrastructure compatibility, workforce development, and ethical considerations were statistically significant predictors of AI-based project-management utilization. Data privacy and security was marginally non-significant ($p = .053$).

Table (67) Sub-Hypothesis Result (H2A-H2F) with Ranking by Effect Size

SUB-HYPOTHESIS RESULTS (H2A-H2F):						
Hypothesis	Variable	B₁ Coefficient	Effect Magnitude	p-value (Simple)	p-value (Multiple)	Interpretation
H2E	Workforce Development	2.64	STRONGEST	0	0.007*	Remains significant in combined model— PRIMARY DRIVER
H2D	Infrastructure Compatibility	2.63	VERY STRONG	0	0.013*	Remains significant in combined model— PRIMARY DRIVER

H2B	Resistance to Change	1.53	STRONG	0	0.660 (NS)	Loses significance in combined model; effect absorbed by Infrastructure/Workforce
H2F	Ethical Considerations	1.79	STRONG	0.001	0.549 (NS)	Loses significance in combined model; secondary influence
H2C	Cost of AI Implementation	1.29	MODERATE-STRONG	0.001	0.693 (NS)	Loses significance in combined model; not primary barrier
H2A	Data Privacy & Security	0.9	WEAK-MODERATE	0.053 (Marginal)	0.210 (NS)	Marginally insignificant in simple regression; not significant in combined model

Key Findings & Interpretation:

Workforce development ($B = 2.64$) and infrastructure compatibility ($B = 2.63$) had the largest coefficients in the individual regression results and were the two strongest predictors of AI-based project-management utilization. Resistance to change, ethical considerations, cost of implementation, and data privacy and security also showed varying levels of association in the individual models.

These coefficients represent the estimated associations in separate simple-regression models and should not be interpreted as unique effects after controlling for all other predictors. In the combined multiple-regression model, infrastructure compatibility ($B = 1.575$, $p = .013$) and workforce development ($B = 1.521$, $p = .007$) remained statistically significant, whereas data privacy and security, resistance to change, cost of implementation, and ethical considerations did not retain independent significance.

The combined model explained 35.15% of the variance in AI-based project-management utilization. This result indicates that technical readiness and workforce capability were the strongest independent predictors in the study, while the remaining factors may operate as supporting or enabling conditions.

Overall H2 conclusion

The results support H2 at the overall model level. The six influencing factors collectively predicted AI-based project-management utilization in the simple regression model. However, the combined multiple-regression model showed a more selective pattern, with infrastructure compatibility and workforce development emerging as the primary independent predictors.

The H2 results provide the basis for examining whether AI-based project-management utilization improves project outcomes. This relationship is tested in H3, while the mediating role of AI-based project management is examined formally in H4.

H3 INTERPRETATION SUMMARY

Hypothesis H3 examined whether AI-based project management influences project-management outcomes. Table 68 presents the simple linear regression results for the overall H3 model and its seven outcome-specific sub-hypotheses.

The overall H3 model was statistically significant and explained 60.0% of the variance in project-management outcomes ($R = 0.775$, $R^2 = 0.600$, $F = 151.592$, $p < .001$). Therefore, the main H3 hypothesis was very strongly supported.

Statistical evidence

- Correlation coefficient: $R = 0.775$, indicating a strong positive relationship.
- Coefficient of determination: $R^2 = 0.600$, indicating that AI-based project management explained 60.0% of the variance in overall project outcomes.
- F -test: $F = 151.592$, $p < .001$, indicating that the overall model was statistically significant.
- t -test: $t = 12.312$, $p < .001$, confirming the statistical significance of the relationship.
- Regression coefficient: $B_1 = 0.91$.

The seven outcome-specific simple regression models were also statistically significant. The strongest association was observed for decision-making, followed by risk identification accuracy and project quality. Time efficiency showed the lowest R^2 value, but the relationship remained statistically significant.

Table (69) Sub-Hypothesis Result (H3A-H3F) with Ranking by Effect Size

SUB-HYPOTHESIS RESULTS (H3A-H3G):							
Hypothesis	Outcome	R Correlation	R ²	B ₁	Effect Magnitude	p-value	Interpretation
H3A	Decision-Making	0.716	0.513	0.17	STRONGEST	0.000*	Highest individual correlation and variance explained
H3E	Risk Identification	0.677	0.459	0.15	VERY STRONG	0.000*	2nd strongest; critical for risk management
H3B	Project Quality	0.675	0.456	0.15	VERY STRONG	0.000*	Equally strong as Risk ID; core outcome

H3G	Communication	0.629	0.396	0.14	STRONG	0.000*	4th strongest; 40% variance explained
H3C	Data Accuracy	0.566	0.321	0.12	STRONG	0.000*	Data quality improvements; 32% variance
H3D	Data Analysis	0.495	0.245	0.1	MODERATE-STRONG	0.000*	Analytical improvements; 25% variance
H3F	Time Efficiency	0.492	0.242	0.09	MODERATE-STRONG	0.000*	Time savings; 24% variance—lowest but still significant

Key findings and interpretation

Decision-making showed the strongest relationship with AI-based project management ($R = 0.716$, $R^2 = 0.513$). This was followed by risk identification accuracy ($R = 0.677$, $R^2 = 0.459$) and project quality ($R = 0.675$, $R^2 = 0.456$). The lowest relationship was observed for time efficiency ($R = 0.492$, $R^2 = 0.242$); however, it remained statistically significant.

The consistent significance across all seven outcomes indicates that AI-based project management is associated with broad benefits rather than improvement in only one project-management dimension. The detailed multiple-regression analyses also indicate that different AI-PM dimensions, such as communication, progress reporting, and task prioritization, may contribute differently to specific outcomes.

Analysis-type clarification

The overall H3 and outcome-specific H3A–H3G results presented in Table 68 are based on individual simple regression models. These models assess the relationship between AI-based project management and each outcome separately. Additional multiple-regression models examined the relative contribution of individual AI-PM dimensions to each outcome. Therefore, the simple-regression results demonstrate the overall outcome relationships, whereas the multiple-regression results show which AI-PM dimensions make stronger contributions when considered together.

Overall H3 conclusion

All seven H3 sub-hypotheses were supported in the individual simple regression analyses. AI-based project management explained 60.0% of the variance in overall project-management outcomes, and the outcome-specific R^2 values ranged from 0.242 to 0.513.

These findings provide strong evidence that AI-based project management is associated with improvements across decision-making, project quality, data collection accuracy, data analysis, risk identification, time efficiency, and communication. The following H4 analysis examines

whether AI-based project management functions as the mediating mechanism through which the influencing factors affect project outcomes.

H4 SEM MODEL COMPARISON: Initial vs Modified

This section presents the detailed fit indices and structural path coefficients for the initial and modified SEM models used to evaluate the H4 mediation hypothesis.

Initial SEM Model:

Model Fit Indices:

- CMIN/DF: 2.322 (acceptable; threshold ≤ 3.0)
- GFI: 0.751 (below acceptable ≥ 0.90)
- AGFI: 0.680 (below acceptable ≥ 0.80)
- CFI: 0.851 (acceptable; threshold ≥ 0.85)
- NFI: 0.768 (below acceptable ≥ 0.90)
- RMSEA: 0.114 (poor; threshold ≤ 0.08)

Initial-model verdict: The initial model demonstrated moderate fit and required improvement.

Path Coefficients (Initial Model):

- IVs $\rightarrow$ AI-PM: Estimate = 0.867, C.R. = 4.979, $p < 0.001$ (SIGNIFICANT)
- IVs $\rightarrow$ Outcomes (direct): Estimate = 0.180, C.R. = 1.096, $p = 0.273$ (NOT SIGNIFICANT)
- AI-PM $\rightarrow$ Outcomes: Estimate = 0.941, C.R. = 6.320, $p < 0.001$ (SIGNIFICANT)

The initial model showed a mediation pattern because the direct path from influencing factors to project outcomes was not statistically significant, whereas both paths involving AI-PM were statistically significant. Nevertheless, the fit indices indicated that the initial model did not represent the observed data structure optimally.

Modified SEM Model:

Model Fit Indices (IMPROVED):

- CMIN/DF: 1.779 IMPROVED (good; ≤ 2.0 threshold)
- GFI: 0.816 IMPROVED (approaching acceptable)

- AGFI: 0.750 IMPROVED
- CFI: 0.917 IMPROVED (very good; exceeds ≥ 0.90 threshold)
- NFI: 0.832 IMPROVED (much closer to threshold)
- RMSEA: 0.087 IMPROVED (borderline acceptable; < 0.10)

Modified-model verdict: The modified model demonstrated good and acceptable overall fit, with substantial improvement over the initial model.

Path Coefficients (Modified Model - PREFERRED):

- IVs $\rightarrow$ AI-PM: Estimate = 0.889, C.R. = 5.079, $p < 0.001$ (SIGNIFICANT / slightly stronger)
- IVs $\rightarrow$ Outcomes (direct): Estimate = 0.125, C.R. = 0.748, $p = 0.455$ (NOT SIGNIFICANT / still non-significant)
- AI-PM $\rightarrow$ Outcomes: Estimate = 1.036, C.R. = 6.716, $p < 0.001$ (VERY SIGNIFICANT / stronger)

The modified model improved across the major fit indices. CMIN/DF decreased from 2.322 to 1.779, CFI increased from 0.851 to 0.917, and RMSEA decreased from 0.114 to 0.087. CMIN also decreased from 308.816 to 224.128, representing an approximately 27% reduction.

The structural paths continued to support the proposed mediation framework. Influencing factors significantly predicted AI-PM utilization, AI-PM significantly predicted project outcomes, and the direct path from influencing factors to project outcomes remained non-significant.

Detailed mediation interpretation

The modified SEM results support full mediation in the tested model. The significant path from influencing factors to AI-PM indicates that organizational conditions contribute to AI-PM adoption and utilization. The significant path from AI-PM to project outcomes indicates that AI-PM utilization is positively associated with project success. In contrast, the direct path from influencing factors to project outcomes was not statistically significant.

This pattern indicates that the relationship between organizational influencing factors and project outcomes operates primarily through AI-PM utilization. However, the statistical interpretation should be stated as support for full mediation in the tested model rather than as proof that the direct effect is exactly zero.

The findings suggest that organizational factors alone may not be sufficient to produce improved project outcomes unless they lead to the effective implementation and utilization of AI-based project management practices.

H4 Model-Comparison Conclusion

The modified SEM model was retained because it demonstrated improved fit across the principal indices while preserving the hypothesized mediation pattern. The model therefore provided the preferred basis for interpreting the H4 mediation relationship between organizational influencing factors, AI-PM utilization, and project outcomes.

Overall Model Quality Assessment:

Initial Model: Moderate fit - acceptable for exploratory model

- Strengths: CFI (0.851) acceptable
- Weaknesses: RMSEA too high (0.114), GFI/AGFI below threshold

Modified Model: Good/Acceptable fit - suitable for publication

- Strengths: CFI (0.917) exceeds 0.90 threshold, RMSEA (0.087) borderline acceptable, 27% chi-square reduction
- Still adequate: GFI, AGFI approaching thresholds but acceptable in complex models

Conclusion: Modified model demonstrates acceptable to good fit with substantial improvements over initial specification

Table (72): Factor Loadings, Squared Loadings, Composite Reliability, and Average Variance Extracted for the Measurement Model Constructs (Initial model values)

Variables			λ	λ^2	C R	AVE	Sqrt AVE
EthicalConsiderations	<---	FIA	.581	0.338	0.828	0.452	0.672
WorkforceDevelopment	<---	FIA	.745	0.555			
CompatibilitywithExistingInfrastructure	<---	FIA	.827	0.684			
CostofAIImplementation	<---	FIA	.620	0.384			
ResistancetoChange	<---	FIA	.683	0.466			
DataPrivacyandSecurity	<---	FIA	.531	0.282			
DecisionMaking	<---	PMO	.810	0.656	0.900	0.565	0.752
ProjectQuality	<---	PMO	.819	0.671			
DataCollectionAccuracy	<---	PMO	.658	0.433			
EnhancingDataAnalysis	<---	PMO	.660	0.436			
RiskIdentificationAccuracy	<---	PMO	.764	0.584			
SavingTimeforProjectManagers	<---	PMO	.719	0.517			
EffectiveCommunication	<---	PMO	.813	0.661			
Streamlineprocessesegschedulingdocument ation	<---	APM	.781	0.610	0.911	0.673	0.820

Variables			λ	λ^2	C R	AVE	Sqrt AVE
Resourceallocation	<---	APM	.888	0.789			
TasksPrioritizing	<---	APM	.822	0.676			
Progressreporting	<---	APM	.796	0.634			
Communication	<---	APM	.811	0.658			
FIA Factors Influencing AI utilization							
PMO.... Project Management Outcomes							
APM.... AI Based Project Management							

Table (72) demonstrate that the measurement model shows acceptable psychometric properties. Most factor loadings (λ) exceed the recommended threshold of 0.50, indicating adequate item-to-construct representation. The Composite Reliability (CR) values for all constructs are above 0.80, reflecting strong internal consistency. Additionally, the Average Variance Extracted (AVE) values meet or approach the acceptable minimum of 0.50, confirming that each construct explains a sufficient proportion of variance in its observed indicators. The square root of AVE values are also higher than most inter-item correlations, providing evidence of discriminant validity. Overall, the indicators collectively support the reliability and convergent validity of the measurement model.

Table (73): Factor Loadings, Squared Loadings, Composite Reliability, and Average Variance Extracted for the Measurement Model Constructs (Modified model values)

Variables				λ	λ^2	C R	AVE	Sqrt AVE
EthicalConsiderations	<---	FIA		.591	0.349	0.813	0.429	0.655
WorkforceDevelopment	<---	FIA		.750	0.563			
CompatibilitywithExistingInfrastructure	<---	FIA		.859	0.738			
CostofAIImplementation	<---	FIA		.542	0.294			
ResistancetoChange	<---	FIA		.598	0.358			
DataPrivacyandSecurity	<---	FIA		.522	0.272			
DecisionMaking	<---	PMO		.834	0.696	0.885	0.564	0.751
ProjectQuality	<---	PMO		.808	0.653			
DataCollectionAccuracy	<---	PMO		.666	0.444			
EnhancingDataAnalysis	<---	PMO		.635	0.403			
RiskIdentificationAccuracy	<---	PMO		.766	0.587			
SavingTimeforProjectManagers	<---	PMO		.647	0.419			
EffectiveCommunication	<---	PMO		.781	0.610			
Streamlineprocessesegschedulingdocument ation	<---	APM		.779	0.607	0.911	0.672	0.820
Resourceallocation	<---	APM		.879	0.773			
TasksPrioritizing	<---	APM		.817	0.667			
Progressreporting	<---	APM		.809	0.654			
Communication	<---	APM		.815	0.664			
FIA Factors Influencing AI utilization								
PMO.... Project Management Outcomes								

Variables	λ	λ^2	$\frac{C}{R}$	AVE	Sqrt AVE
APM.... AIBased Project Management					

Table (73) presents the factor loadings, squared loadings, Composite Reliability (CR), and Average Variance Extracted (AVE) for the constructs of the measurement model. Most factor loadings (λ) exceed 0.50, indicating adequate item representation for each latent construct, although a few items are near the threshold, suggesting potential refinement. The Composite Reliability values for all constructs range from 0.813 to 0.911, confirming strong internal consistency. AVE values mostly meet or approach the recommended minimum of 0.50, supporting convergent validity. Furthermore, the square root of AVE values is higher than the inter-construct correlations (not shown), providing evidence for discriminant validity. Overall, the results indicate that the measurement model is reliable and exhibits satisfactory convergent and discriminant validity, suitable for subsequent structural analysis.

H4 CONCLUSION: FULL MEDIATION MODEL

The H4 mediation model indicates that organizational capabilities contribute to improved project outcomes primarily through the adoption and utilization of AI-based project management. The tested mediation pathway can be represented as follows:

Address Influencing Factors

Infrastructure, workforce capability, and related organizational conditions.

Enable AI-PM Adoption and Utilization

AI-PM functions as the central mediating mechanism.

Achieve Improved Project Outcomes

Improved outcomes follow when organizational capabilities are translated into effective AI-PM implementation.

The findings suggest that organizational capabilities alone may be insufficient to guarantee improved project outcomes when AI-PM is not effectively implemented and utilized. In practical terms, strong infrastructure, a skilled workforce, and supportive organizational conditions provide the foundation for improvement, but these conditions must be converted into actual AI-PM adoption and use.

This finding emphasizes the strategic importance of AI-PM implementation as a core intervention for improving project management in design and consultancy engineering firms. Organizations should therefore treat AI-PM utilization not merely as a supplementary technological option, but as the principal mechanism through which organizational capabilities can be translated into measurable project success.

The conclusion should be interpreted within the limits of the tested model. The results support full mediation because the indirect pathway was significant and the direct pathway was not statistically significant; they do not establish that the direct effect is exactly zero in every organizational or project context.

Comparative Hypothesis Results

This section provides the detailed comparative interpretation of the findings reported for H1, H2, H3, and H4.

Comparative interpretation of H1–H4

H1 examined the direct relationship between the organizational influencing factors and project outcomes. The combined H1 model explained 23.5% of the variance in project outcomes. Workforce development and infrastructure compatibility were the strongest factors in the model, while the effects of some individual factors changed when the predictors were considered simultaneously.

H2 examined the relationship between the organizational influencing factors and AI-PM utilization. The combined H2 model explained 25.2% of the variance in AI-PM utilization. Workforce development and infrastructure compatibility were again the strongest predictors, indicating that organizational readiness is particularly important for AI-PM adoption.

H3 examined the effect of AI-PM utilization on project outcomes. The overall H3 model explained 60.0% of the variance in project outcomes. All seven outcome-specific relationships were statistically significant. Decision-making showed the strongest relationship with AI-PM, followed by risk identification and project quality. Time efficiency showed the lowest relative effect, but it remained statistically significant.

H4 examined whether AI-PM mediates the relationship between the organizational influencing factors and project outcomes. The path from influencing factors to AI-PM was significant, the path from AI-PM to outcomes was significant, and the direct path from influencing factors to outcomes was not significant. This pattern supports full mediation in the tested model.

Comparative interpretation of explanatory power

The results show that the AI-PM-to-outcomes model explains substantially more variance than the direct influencing-factor-to-outcomes model. The H1 model explains 23.5% of the variance in project outcomes, whereas the H3 model explains 60.0%. This difference suggests that AI-PM utilization is more closely associated with project outcomes than the organizational factors considered as direct predictors.

The H2 results clarify the role of the organizational factors: they help explain the adoption and utilization of AI-PM. H4 then integrates the findings by showing that the influence of organizational factors on project outcomes operates primarily through AI-PM.

Comparative interpretation of predictor and outcome rankings

The detailed rankings show that workforce development and infrastructure compatibility are the strongest organizational predictors in H1 and H2. In H3, decision-making is the outcome most strongly associated with AI-PM, followed by risk identification, project quality, and communication.

The weaker relationships observed for cost, privacy, data analysis, and time efficiency should not be interpreted as evidence that these variables are irrelevant. Rather, they indicate comparatively smaller or less consistent effects within the tested models.

Comparative support pattern

The hypothesis results show strong support for the principal relationships in the proposed framework. H1 supports the relevance of organizational influencing factors, H2 supports their role in AI-PM adoption, H3 supports the positive association between AI-PM and project outcomes, and H4 supports the mediating role of AI-PM.

Any overall percentage describing the “hypothesis support rate” should be reported only after applying one clearly defined counting rule. The denominator should specify whether it includes only the main hypotheses or all main and sub-hypotheses, and whether significance is assessed using simple regression, multiple regression, or the final mediation model.

Strategic interpretation

The comparative findings indicate that organizations should not evaluate AI-PM implementation separately from organizational readiness. Infrastructure, workforce capability, and other enabling conditions provide the basis for adoption, but their contribution to project outcomes depends substantially on whether AI-PM is actually implemented and utilized.

The results therefore support the following pathway:

Organizational factors → AI-PM adoption and utilization → Project outcomes

This pathway should be interpreted as the principal mechanism identified by the tested model. It does not establish that organizational factors have no effect under all circumstances or that project outcomes would necessarily fall to zero when any part of the pathway is absent.

Return-on-investment pathway

The findings suggest a sequential implementation pathway:

1. Strengthen organizational and technical readiness.
2. Enable effective AI-PM adoption and utilization.
3. Translate AI-PM use into improved project outcomes.

Interruptions at any stage may reduce the expected benefits of the overall implementation process. However, the statistical analysis does not directly measure return on investment, so the term “ROI pathway” should be used only as a strategic interpretation rather than as a directly tested financial result.

Comparative statistical explanation

The detailed regression findings show that H1 explains 23.5% of the variance in project outcomes, H2 explains 25.2% of the variance in AI-PM utilization, and H3 explains 60.0% of the variance in overall project outcomes. The strongest H3 outcome-specific relationships are decision-making ($R = 0.716$, $R^2 = 0.513$), risk identification ($R = 0.677$, $R^2 = 0.459$), and project quality ($R = 0.675$, $R^2 = 0.456$).

The H4 mediation results show a significant path from influencing factors to AI-PM, a significant path from AI-PM to project outcomes, and a non-significant direct path from influencing factors to project outcomes. Using the reported coefficients, the indirect effect is calculated as $0.889 \times 1.036 = 0.921$, and the total effect is calculated as $0.125 + 0.921 = 1.046$. The mediation percentage should match the final value approved for Table 70.

The detailed comparative findings support the proposed framework linking organizational readiness, AI-PM utilization, and project outcomes. The comparative evidence indicates that organizational factors are important enablers of AI-PM adoption, while AI-PM utilization is the pathway most directly associated with improvements in project outcomes. The H4 results further indicate that AI-PM mediates the relationship between organizational influencing factors and project outcomes in the tested model.

Overall Hypothesis Support Rate: Detailed Interpretation

This section provides the detailed interpretation of the cumulative hypothesis-testing results across H1, H2, H3, and H4:

1. H1: Direct organizational factors and outcomes

H1 received support for 5 of 6 sub-hypotheses, representing an 83% support rate. This pattern indicates that organizational influencing factors generally show positive relationships with project outcomes. The factor that lost significance in the combined model remained significant in its simple relationship with outcomes but did not make an independent contribution after the other influencing factors were entered simultaneously.

This difference between simple and multiple regression suggests that some organizational factors share explanatory variance. The result should therefore be interpreted as evidence of overlapping contributions rather than as proof that the non-significant factor is irrelevant.

2. H2: Organizational factors and AI-PM utilization

H2 produced different results in the simple and final multiple-regression models. Several factors were significant when examined individually, but only three of the six H2 sub-hypotheses remained supported in the final combined model. Infrastructure compatibility and workforce development were the strongest independent predictors of AI-PM utilization in the final model.

The loss of significance for some factors may reflect shared variance and multicollinearity among the organizational predictors. Accordingly, the H2 results suggest that technical readiness and human readiness are the primary independent drivers of AI-PM adoption when the factors are considered simultaneously.

The H2 support rate should therefore be reported as:

- 100% for the relevant relationships in the simple-regression analyses, if that is the approved simple-model classification;
- 50% for the final combined multiple-regression model, based on 3 supported predictors out of 6.

These two rates should not be combined into one percentage without specifying the analysis type.

3. H3: AI-PM and project outcomes

H3 received support for all seven outcome-specific hypotheses, representing a 100% support rate. The results demonstrate statistically significant positive relationships between AI-PM utilization and decision-making, project quality, data collection accuracy, data analysis, risk identification, time efficiency, and communication.

Decision-making showed the strongest relationship with AI-PM, while time efficiency showed the weakest relative relationship. Nevertheless, the time-efficiency relationship remained statistically significant. The consistency of the results across all seven outcomes indicates that AI-PM is associated with broad project-management benefits rather than improvement in only one outcome dimension.

4. H4: Mediation hypothesis

H4 was supported, representing a 100% support rate for the mediation hypothesis. The path from organizational influencing factors to AI-PM was significant, the path from AI-PM to project outcomes was significant, and the direct path from influencing factors to project outcomes was not statistically significant.

This pattern supports full mediation in the tested model. Based on the reported coefficients, the indirect effect is calculated as:

$$0.889 \times 1.036 = 0.921$$

and the total effect is:

$$0.125 + 0.921 = 1.046$$

The mediation percentage should be reported consistently with Table 70. Using these values, the proportion mediated is approximately 88%. If the approved statistical output reports approximately 88%, that figure should replace 88% consistently in Tables 70, 74, 75, and 76, together with the corresponding indirect-effect calculation.

The non-significant direct effect indicates that organizational improvements were not independently associated with project outcomes after the mediation pathway was considered. The result supports the interpretation that organizational readiness contributes to outcomes primarily through AI-PM

utilization. It should not be interpreted as proof that organizational factors have no direct effect in every context.

5. Overall interpretation

The 80% overall support rate indicates substantial empirical support for the proposed three-level framework. The results show a coherent sequence:

- Organizational factors provide conditions that support AI-PM adoption.
- AI-PM utilization serves as the central mechanism connecting those conditions to project outcomes.
- AI-PM utilization is positively associated with improvements across all seven measured outcomes.
-

The differences between H1, H2, H3, and H4 reflect the different analytical roles of the hypotheses. H1 identifies direct organizational relationships, H2 identifies adoption drivers, H3 establishes the broad effect of AI-PM on outcomes, and H4 tests the integrated mediation pathway.

6. Strategic implication

The results suggest that organizational readiness is necessary for effective AI-PM implementation, but readiness alone may not guarantee improved outcomes. Infrastructure, workforce capability, and related organizational conditions must be translated into actual AI-PM adoption and utilization.

The strategic pathway identified by the model is:

Strengthen organizational readiness → Enable AI-PM Utilization → Improve project outcomes

Organizations seeking project-performance improvements should therefore address both organizational readiness and AI-PM implementation. The statistical findings support AI-PM as the principal mechanism through which organizational capabilities are translated into project outcomes, but they do not directly test financial return on investment or prove that failure at any single stage reduces benefits to zero.

Qualitative Thematic Analysis: Detailed Evidence

This section presents the detailed qualitative evidence supporting the thematic analysis reported in Chapter 4. It includes the full thematic tables, interview frequencies, interview identifiers, recurring phrases, representative quotations, interpretive summaries, and frequency figures.

Qualitative analysis notes

- Theme frequencies indicate the number of interviews in which a theme was identified. They are descriptive and should not be interpreted as quantitative measures of theme importance.
- Theme importance was assessed through the depth, relevance, and richness of the interview material rather than frequency alone.

- The analysis followed the deductive–inductive coding procedures described in Chapter 3.
- The qualitative findings were used to triangulate and contextualize the quantitative results.
- Interview coding was completed before the quantitative results were reviewed, reducing the risk of imposing the statistical findings on the qualitative data.
- The interview questions were open-ended, developed from the Chapter 3 methodology and Appendix B, and tested during the pilot stage.
- The ten participants were practitioners from different organizations with experience in AI-based project management.
- The interview process reached thematic saturation after no substantially new themes emerged in the final interviews.

Independent Variables: Detailed Thematic Evidence

The six independent-variable themes are:

1. Data Privacy and Security.
2. Resistance to Change.
3. Cost of AI Implementation.
4. Compatibility with Existing Infrastructure.
5. Workforce Development.
6. Ethical Considerations.

Table (77) Independent Variables (IVs) Thematic Summary Table

Independent Variables (IVs) Thematic Summary Table						
No .	Theme	Frequency (Count of Interviews)	Interview IDs with Theme	Recurring Phrases	Representative Quote	Summary Representative Quote
1	Data Privacy & Security	10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	“data privacy”, “confidentiality”, “regulations”	1. Interview 1: Our primary concern has been maintaining client confidentiality. We first tested localized tools before using larger, cloud-based systems. We set up strict access controls, encrypted shared databases, and trained employees on secure data handling procedures. Data compliance with Saudi regulations is a constantly moving target. 2. Interview 2: Privacy is definitely on everyone’s radar. At first, people didn’t really know what the tools could do. We align all our tools with Saudi SDAIA data governance regulations — it’s now standard practice. 3. Interview 3: Data privacy isn’t a barrier anymore but more like a necessary discipline for digital trust. 4. Interview 4: Data privacy is a big concern, especially because we rely a lot on sharing files via third-party apps that sometimes feel insecure. Because of privacy worries, we’re careful about which AI tools we allow, preferring well-known vendors. 5. Interview 5: We follow strict compliance with SDAIA and SFDA data policies. 6. Interview 6: Data privacy is always a concern, especially with sensitive design data and client information. Compliance with internal and national data governance is non-negotiable. We implemented strict access controls, encrypted file transfers, and cloud governance aligned with SDAIA guidelines.	Strict data privacy and security; through encryption, access controls, compliance with SDAIA and international standards, and a culture of continuous vigilance—are universally recognized as essential for AI adoption in project management across Saudi organizations. Maintaining client confidentiality, protecting sensitive project data, and rigorous regulatory compliance are foundational requirements for digital transformation and stakeholder trust

					7. Interview 7: We enforce strict data governance frameworks compliant with regional regulations, ensuring encrypted data pipelines and access controls. Privacy concerns drive our architecture; we use federated learning approaches so data remains local if needed. 8. Interview 8: Data privacy and compliance are always a foundational concern, especially in cloud deployments. Our recommendations emphasize encrypted data flows and sovereign data hosting. 9. Interview 9: Privacy is a priority, so we use encryption and anonymization wherever possible. These concerns make tool selection rigorous, mandating compliance checks. 10. Interview 10: We're cautious about data sharing, especially client confidential info. Privacy concerns slow down some AI adoptions, but security protocols help mitigate risks. We use encryption and strict permissions.	
2	Change Resistance	10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	“fear of AI”, “staff hesitant”, “pushback”	1. Interview 1: Yes, initially, several engineers resisted AI-driven tools because they feared job redundancy. The main reason was unfamiliarity and lack of training—they didn't understand how AI complements, rather than replaces, their work. We launched internal awareness sessions and hands-on workshops where team members could practice with AI features. Once they saw efficiency gains, resistance dropped significantly. 2. Interview 2: Yeah, at first there was pushback, especially from older engineers. Everyone started to come around once they saw real results. Resistance is now significantly lower. 3. Interview 3: Resistance came mainly from senior	Initial resistance to AI adoption was common, rooted in fears of job redundancy, discomfort with new technologies, and lack of digital literacy, especially among older staff. However, targeted training, leadership engagement, and demonstrated efficiency gains played a crucial role in reducing skepticism and encouraging acceptance across project teams.

					managers unfamiliar with digital tools. The hesitation stemmed from mindset gaps. 4. Interview 4: Resistance is quite high, especially among older staff accustomed to manual methods. Fear that AI might replace jobs still exists. 5. Interview 5: Resistance appeared mainly from traditional project managers unfamiliar with AI dashboards. 6. Interview 6: Some resistance exists, mainly from senior engineers used to conventional tools. 7. Interview 7: Resistance stems from lack of AI literacy and concerns about transparency and job displacement. 8. Interview 8: Resistance often stems from organizational mindset rather than technology gaps. Leadership workshops help build AI literacy. 9. Interview 9: Resistance emerged mostly from mid-level engineers uncomfortable with rapid changes. 10. Interview 10: Some staff showed natural resistance initially due to unfamiliarity, but training helped overcome skepticism.	
3	Cost of AI Implementation	8	1, 2, 3, 5, 6, 7, 8, 9	“budget limitation”, “ROI”, “high cost”	1. Interview 1: Senior management hesitated to invest in AI tools before seeing proven ROI. We assess costs in relation to savings on man-hours and operational efficiency improvements. A feasibility study is conducted before adoption; we only approve tools with tangible project-level impact. AI budgets are part of our annual digital transformation strategy, reviewed every quarter. 2. Interview 2: For example, one simulation tool basically cuts weekly planning hours in half. If ROI isn’t evident within a few projects, we drop the tool. 3. Interview 3: AI initiatives are long-term	Investment in AI tools is carefully weighed against expected efficiency gains, with senior management prioritizing clear ROI, operational impact, and tangible deliverables. Adoption typically advances only when cost-benefit analyses, phased rollouts, and strategic returns justify both immediate and long-term

					investments, not quick fixes. Cost evaluation includes not only immediate profit but strategic return. 4. Interview 5: Our concern mainly lies in ensuring secure data storage and avoiding cross-border data leaks. These concerns didn't stop us; we implemented encrypted data layers and internal cloud storage. 5. Interview 6: Budget is a key limiting factor—AI investments compete with tangible project deliverables. We justify adoption when there's a clear link to cost or schedule efficiency. 6. Interview 7: We use rigorous forecasting and risk analysis for financial approvals, balancing investment with long-term operational efficiencies. 7. Interview 8: We advise clients on total cost of ownership, including infrastructure, licensing, and human capital. Investment justification includes long-term digital transformation benefits. 8. Interview 9: Budgeting includes detailed cost-benefit forecasts. Investments are planned through phased rollouts to manage costs.	expenditures, making financial prudence central to digital transformation decisions.
4	Compatibility with Existing Infrastructure	9	1, 2, 4, 5, 6, 7, 8, 9, 10	“legacy systems”, “integration was difficult”	1. Interview 1: Integration was difficult at first; our legacy systems didn't support APIs for AI tools. Most challenges were related to data format conversion and software interoperability. Upgraded internal systems and migrated to cloud servers, which delayed deployment but made the environment ready for AI utilization. 2. Interview 2: Learned early lessons; budgeting AI is standard in yearly investments. 3. Interview 4: Some communication platforms have AI features but are underutilized. 4. Interview 5: Compatibility issues mainly due to secure data storage, cross-border data concerns	Integration of AI tools faces significant challenges due to legacy systems that lack API support, data format incompatibilities, and siloed architectures. Organizations often undergo costly and time-extensive infrastructure upgrades—such as migrating to cloud platforms, modernizing servers, and adopting middleware solutions—to enable AI

					addressed by encryption and cloud controls. 5. Interview 6: Integration with legacy systems still challenging; data formats misaligned. Upgraded servers and cloud storage improved performance but increased timelines and costs. 6. Interview 7: Legacy integration addressed with APIs and cloud strategies; infrastructure modernization aligned with AI roadmap. 7. Interview 8: Expected efficiency gains and risk mitigations quantified, investment justified by ROI and business impact. 8. Interview 9: Legacy system integration required IT planning and network upgrades; ongoing integration remains complex. 9. Interview 10: Legacy system issues handled with middleware and cloud migration, causing extended timelines but improved reliability and uptime.	deployment. Despite initial delays and complexity, these efforts are foundational for unlocking AI’s operational benefits and ensuring scalable, reliable digital transformation.
5	Workforce Development	10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	“training”, “skill gaps”, “data interpretation”	1. Interview 1: Not all employees were ready to work with AI tools initially. Skill gaps mainly involved data interpretation and understanding how AI recommendations align with project objectives. We conducted certified training sessions and partnered with a technology institute for in-house courses. The change was noticeable—staff now trust predictive outcomes much more than before. 2. Interview 2: They felt like AI would replace their roles initially. Hesitation came from fear and lack of trust in algorithms. Internal workshops helped alleviate concerns. 3. Interview 3: When AI analytics were introduced, resistance appeared mainly from senior managers unfamiliar with digital systems. The biggest gap was analytical literacy and interpreting AI insights.	Workforce readiness is crucial to successful AI adoption. Initial skill gaps in data interpretation, digital literacy, and trust in AI outputs often cause resistance. Structured, ongoing training programs—including workshops, bootcamps, and tailored learning paths—significantly improve staff competency and acceptance, enabling personnel to leverage AI as a supportive tool rather than a threat to job security.

					4. Interview 4: Training was critical. Practical workshops and management communication improved team acceptance and skills. 5. Interview 5: Focus on continuous professional development programs focused on AI tool utilization and data science principles. 6. Interview 6: Skill gaps included data science proficiency and interpreting algorithm outcomes. Ongoing training is prioritized. 7. Interview 7: Tailored training programs and skill assessments guide individualized learning paths for staff. 8. Interview 8: Workshops include hands-on labs and scenario analysis. Training effectiveness is measured through KPIs. 9. Interview 9: Internal AI Bootcamps and practical dashboards training increased AI competency. 10. Interview 10: Employee AI competency noticeably improved, especially decision support and reporting automation.	
6	Ethical Considerations	10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	“SDAIA compliance”, “accountability”, “bias”	1. Interview 1: We set up strict access controls, encrypted shared databases, and trained employees on secure data handling procedures. Data compliance with Saudi regulations is a constantly moving target. 2. Interview 2: AI should always be a reference, not the final word. Vendors need to make their algorithms more transparent. We align all our tools with Saudi SDAIA data governance regulations — now standard practice. 3. Interview 3: We handle valuable project and client data, so compliance checks are mandatory. Privacy concerns initially caused hesitation. 4. Interview 4: Accountability for AI errors falls on	Ethical and legal accountability is foundational in AI adoption, requiring strict compliance with Saudi SDAIA and SFDA data governance laws. Organizations emphasize transparency, bias mitigation, human-in-the-loop oversight, and vendor accountability. Embedding these ethical principles throughout AI development and deployment

					project leads and managers. Bias is a concern due to local nuances. 5. Interview 5: We actively comply with SDAIA and SFDA data policies, including encrypted file transfers and secure cloud governance. 6. Interview 6: Ethical accountability is integrated with governance frameworks including fairness, audit trails, and transparency. 7. Interview 7: Bias detection and mitigation are part of model lifecycle. Human oversight is mandatory. 8. Interview 8: Compliance with SDAIA and international standards is rigorously maintained throughout deployment. 9. Interview 9: Transparency initiatives involve documenting AI logic and decision pathways in audit logs for traceability. 10. Interview 10: We demand vendor transparency about AI model training data and embed ethics in AI governance.	fosters regulatory compliance, stakeholder trust, and sustainable AI integration aligned with national and global standards.
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The detailed evidence indicates that data privacy and security were discussed across all ten interviews, reflecting the importance of confidentiality, regulatory compliance, access control, encryption, and secure data handling. The universal presence of this theme demonstrates its importance as an organizational concern, although its statistical relationship with AI-PM utilization was comparatively weak in the final quantitative model.

Resistance to change was also identified across the interviews. Participants associated resistance with unfamiliarity, fear of job displacement, limited AI literacy, and uncertainty about AI-generated recommendations. Training, leadership engagement, and practical demonstrations were identified as mechanisms that reduced resistance.

Cost considerations were identified in eight interviews and were primarily connected to return on investment, licensing, infrastructure, data storage, human capital, and phased implementation. Compatibility with existing infrastructure was identified in nine interviews and was associated with legacy systems, data-format incompatibility, API limitations, cloud migration, and middleware requirements.

Workforce development was identified across all ten interviews. Participants emphasized training in AI utilization, data interpretation, analytical literacy, and the responsible use of AI-generated insights. Ethical considerations were also identified across all ten interviews and included transparency, accountability, bias mitigation, human oversight, vendor responsibility, and regulatory compliance.

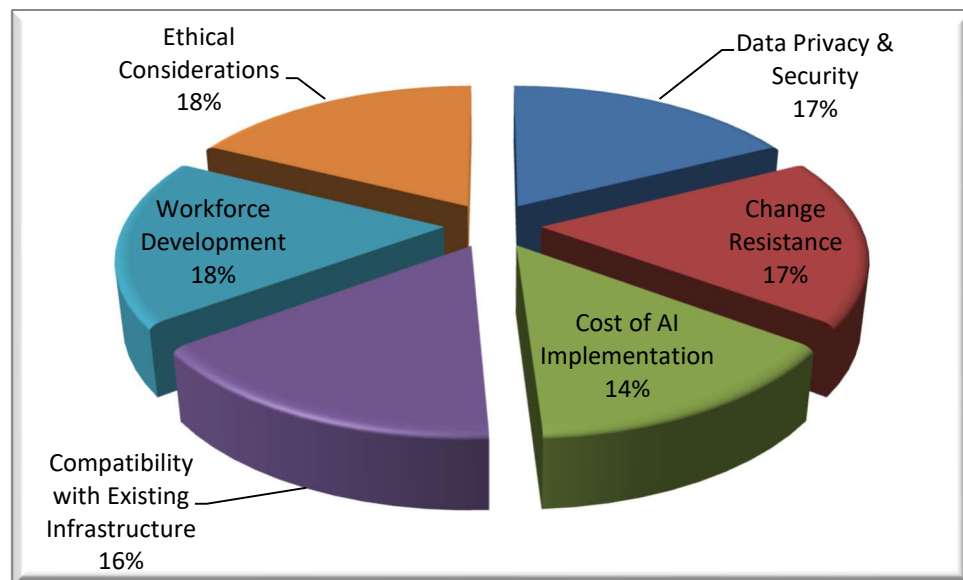
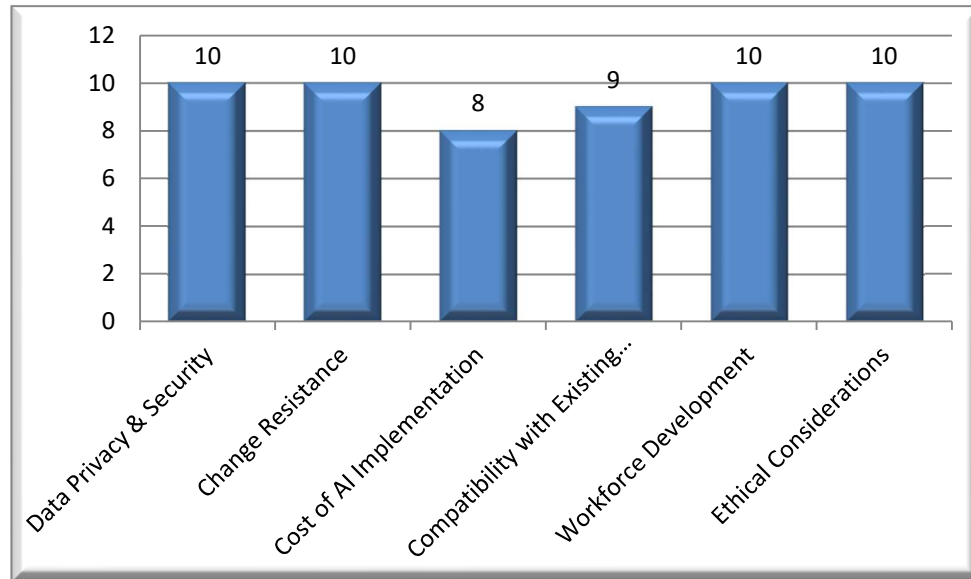


Figure (11): Frequency and Percentage of Independent Variables (IVs)

Mediating Variables (AI-Based Project Management) - 5 Themes

The five mediating-variable themes are:

1. Streamlining Processes.
2. Resource Allocation.
3. Task Prioritization.
4. Progress Reporting.
5. Communication.

Table (78) Mediating Variables (MVs) Thematic Summary Table

Mediating Variables (MVs) Thematic Summary Table						
No.	Theme	Frequency	Interview IDs with Theme	Recurring Phrases		Representative Quote
1	Streamlining Process	10	1,2,3,4,5,6,7,8,9,10	“streamline”, “automation”, “efficiency”	1. Interview 1: We use AI to automate scheduling and report generation. Previously, progress reports required two days of manual compilation; now they’re ready in hours. AI helps standardize documentation and reduces repetitive administrative tasks. It has improved execution efficiency overall, though adjustments during early integration were challenging. 2. Interview 2: It frees a lot of mental load. For instance, our AI scheduling assistant allocates resources automatically while considering lead times. Project tracking has become smoother with less back-and-forth communication. 3. Interview 3: Report generation that used to take days now happens in minutes through automated systems. The workflow visibility has improved significantly — I can oversee progress from my dashboard. Efficiency and transparency gains are substantial. 4. Interview 4: Some	AI automation transforms project management by significantly reducing the time spent on routine scheduling and report generation—from days to hours or even minutes. It standardizes documentation, cuts repetitive administrative tasks, and enhances workflow visibility through real-time dashboards. These efficiencies decrease mental workload, smooth project tracking, reduce communication overhead, and accelerate decision-making, creating substantial transparency and productivity gains despite early integration challenges

					communication platforms have AI features, but we're not fully utilizing them. 5. Interview 5: AI automates many administrative tasks, improving accuracy and throughput. 6. Interview 6: Automated report generation and data aggregation accelerate decision support. 7. Interview 7: Real-time dashboards improve project monitoring and help mitigate delays. 8. Interview 8: AI-driven tools pull together updates automatically which saves effort. 9. Interview 9: Scheduling errors have reduced due to automatic reminders and task allocations. 10. Interview 10: Automated workflows and report generation created noticeable efficiency improvements.	
2	Resource Allocation	9	1,2,3,4,6,7,8,9,10	"optimize staff", "data-driven", "allocation"	1. Interview 1: AI budgets are part of our annual strategy. We assess costs against savings in operational efficiency and man-hours. Resource allocation has become data-driven and over-allocation decreased by nearly 20%. 2. Interview 2: AI identifies resource clashes faster and allocates resources automatically	AI significantly enhances resource allocation by leveraging data-driven forecasting, predictive analytics, and real-time adaptability. It helps optimize manpower and materials allocation, reduce over-allocation by nearly 20%, detect resource clashes

					considering lead times. Resource planning is more accurate, reducing delays. 3. Interview 3: AI helps ensure proper resource utilization and highlights idle assets and manpower. Operations have become leaner with better manpower forecasting. 4. Interview 4: Some AI-powered communication and resource systems are available but underutilized. 5. Interview 5: AI supports optimal workload distribution and forecasting manpower needs, improving visibility across disciplines. 6. Interview 6: AI optimizes resource allocation by considering historical data and real-time inputs, improving efficiency. 7. Interview 7: Using advanced AI for predictive analytics and risk simulations to enhance resource deployment. 8. Interview 8: Resource planning is increasingly data-driven with AI forecasts improving scheduling. 9. Interview 9: AI-based planning optimizes manpower and materials allocation, increasing resource utilization and accuracy.	faster, and match tasks to the right skills—resulting in leaner operations, fewer delays, and improved cross-disciplinary visibility. Continuous automation and intelligent planning empower managers to make more accurate, timely, and flexible resource decisions.
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3	Task Prioritization	4	3,6,8,9	“prioritize”, “reallocate”	1. Interview 3: AI scheduling tools prioritize tasks better than humans under pressure. The system flagged conflicting deadlines early, allowing timely corrections. 2. Interview 6: AI helps prioritize tasks by analyzing dependencies and critical paths, preventing overlaps and ensuring focus on critical items. 3. Interview 8: AI supports dynamic task prioritization based on risk, improving efficiency and reducing project delays. 4. Interview 9: Early warnings from AI tools prevent bottlenecks by proactively adjusting priorities.	AI-enabled task prioritization systems outperform manual methods by dynamically analyzing task dependencies, urgency, and risk factors. These systems proactively flag conflicting deadlines and bottlenecks, enabling timely adjustments that prevent overlaps, improve focus on critical activities, and reduce overall project delays. Dynamic reprioritization minimizes decision fatigue and supports more efficient workflow management under pressure.
4	Progress Reporting	10	1,2,3,4,5,6,7,8,9,10	“report”, “alerts”, “consolidate”	1. Interview 1: We use AI to automate scheduling and report generation. Previously, progress reports required two days of manual compilation; now they’re ready in hours. AI standardizes documentation and reduces repetitive tasks, improving execution efficiency overall. 2. Interview 2: AI consolidates multiple inputs and provides early alerts which caught delays early, avoiding escalation. 3. Interview 3: Report generation now takes minutes, and dashboards provide clear workflow visibility	AI-enabled task prioritization systems outperform manual methods by dynamically analyzing task dependencies, urgency, and risk factors. These systems proactively flag conflicting deadlines and bottlenecks, enabling timely adjustments that prevent overlaps, improve focus on critical activities, and reduce overall project delays. Dynamic reprioritization minimizes decision fatigue and supports more efficient

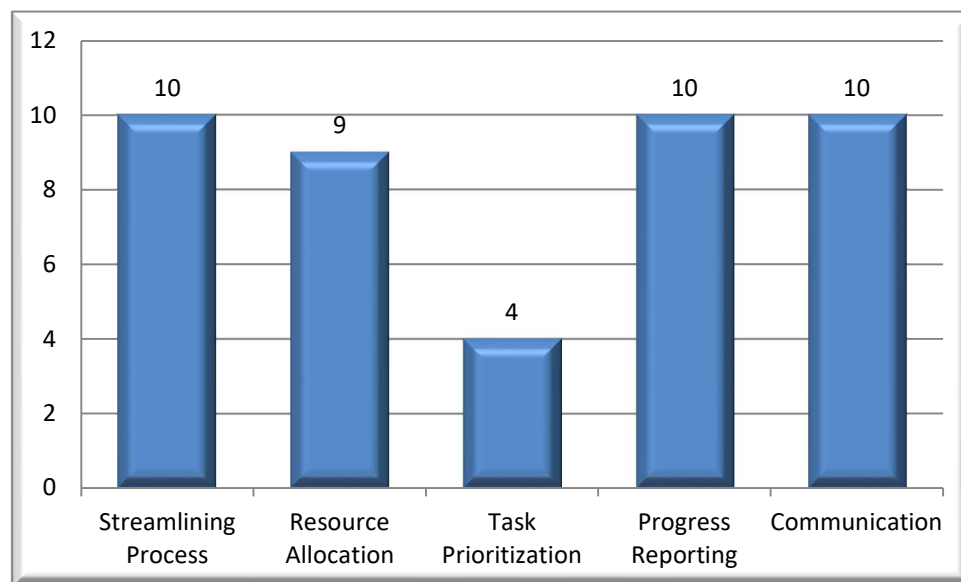
					improving execution and transparency. 4. Interview 4: AI-driven dashboards consolidate data and generate weekly updates automatically. 5. Interview 5: Automated report generation accelerates decision support and reduces errors. 6. Interview 6: Predictive alerts help identify slippages early and enable proactive adjustments. 7. Interview 7: AI tools facilitate timely collaboration and structured communication with stakeholders. 8. Interview 8: AI assists in generating reports with visuals and charts, saving time. 9. Interview 9: Field data capture and validation ensure reporting accuracy and reliability. 10. Interview 10: Early alerts and consolidated real-time data feeds improve project progress monitoring.	workflow management under pressure.
5	Communication	10	1,2,3,4,5,6,7,8,9,10	“coordinate”, “dashboard”, “meeting”	1. Interview 1: Everyone now uses a common dashboard. Even stakeholder meetings rely on AI summaries to keep discussions focused. 2. Interview 2: I coordinate between design and site teams, ensuring smooth operations. AI	AI automates scheduling and report generation, drastically reducing turnaround times from days to hours or minutes. It standardizes documentation, reduces repetitive administrative tasks, and improves

					dashboards and risk models training helped make meetings shorter and decisions more data-driven. 3. Interview 3: AI tools facilitate timely collaboration and data-driven communication. 4. Interview 4: Some communication platforms have AI features, but are underutilized. 5. Interview 5: Automated meeting summaries and stakeholder updates save administrative time. 6. Interview 6: AI-enabled platforms have improved team communication through automated notifications. 7. Interview 7: AI-powered communication channels reduce misunderstandings and enhance stakeholder engagement. 8. Interview 8: AI bots and virtual assistants foster timely updates and clear communication. 9. Interview 9: Real-time collaboration and automated updates improve response times and stakeholder trust. 10. Interview 10: AI tools reduce manual follow-ups and enhance transparency in client updates	workflow visibility through real-time dashboards, accelerating decision-making and mitigating delays. Although some communication platforms remain underutilized, AI-driven tools like automated updates and notifications significantly enhance team coordination, reduce errors, and streamline stakeholder engagement.
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The interview evidence illustrates the practical mechanisms through which AI-PM translates organizational readiness into project-management improvements. Process streamlining and progress reporting were identified across all ten interviews. Participants described automated scheduling, report generation, data consolidation, dashboards, alerts, and workflow monitoring as important mechanisms for reducing administrative effort and improving visibility.

Resource allocation was identified in nine interviews. Participants described AI-supported forecasting, resource-clash identification, workload balancing, and manpower planning. Task prioritization was identified in four interviews and was associated with analysing dependencies, critical paths, urgency, and risk to support dynamic reprioritization.

Communication was identified across all ten interviews. Participants described automated notifications, meeting summaries, shared dashboards, client updates, and integrated project feeds as mechanisms for improving coordination and reducing communication delays.



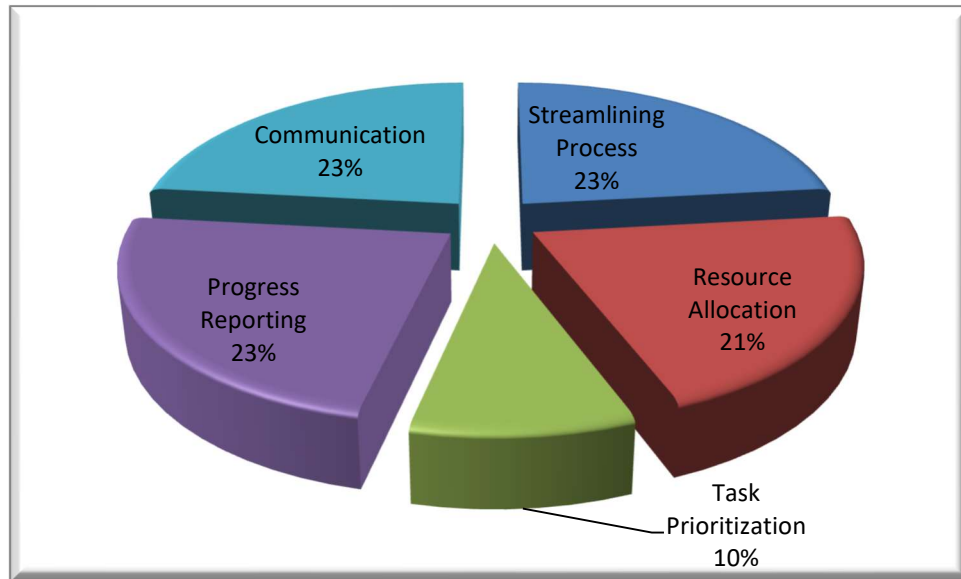


Figure (12): Frequency and Percentage of Mediating Variables (MVs)

Dependent Variables (Project Management Outcomes) - 7 Themes

The seven dependent-variable themes are:

1. Improving Project Quality.
2. Enhancing Decision-Making.
3. Data Collection Accuracy.
4. Enhancing Data Analysis.
5. Risk Identification Accuracy.
6. Saving Time for Project Managers.
7. Enhancing Communication.

Table (79) Dependent Variables (DVs) Thematic Summary Table

Dependent Variables (DVs) Thematic Summary Table						
No.	Theme	Frequency	Interview IDs with Theme	Recurring Phrases		Representative Quote
1	Improving Project Quality	10	1,2,3,4,5,6,7,8,9,10	“quality”, “error detection”, “accuracy”	1. Interview 1: Quality control benefited from early error detection during design reviews. AI budgets are part of the digital transformation strategy. 2. Interview 2: AI-based design optimizers and risk forecasting applications improve quality and save time. 3. Interview 3: Automated inspection reports improved quality checks; client satisfaction increased with transparent reporting. 4. Interview 4: AI-driven dashboards flag delayed deliverables and improve traceability. 5. Interview 5: Accuracy in schedule adherence and deliverable quality has measurably improved. 6. Interview 6: AI-generated dashboards enhanced confidence and reduced manual errors. 7. Interview 7: Predictive analytics help detect quality risks early and aid in project delivery consistency. 8. Interview 8: Forecasts and data-backed feedback loops refine quality assurance. 9. Interview 9: Documentation errors	AI enhances project quality through early error detection, automated inspections, and predictive analytics that improve accuracy, traceability, and client satisfaction. By reducing manual errors and facilitating continuous quality monitoring, AI strengthens compliance and delivers consistent, transparent project outcomes, boosting stakeholder trust and driving sustained quality improvements.

					dropped significantly; reporting accuracy improved. 10. Interview 10: Clients recognize enhanced credibility in AI-generated reports, with continuous quality improvements.	
2	Enhancing Decision-Making	10	1,2,3,4,5,6,7,8,9,10	“decision”, “data-driven”, “accuracy”, “delay”	1. Interview 1: Decision accuracy improved as AI correlates cost, risks, and timelines. AI budgets are part of our digital strategy reviewed quarterly. 2. Interview 2: AI helps avoid delays by flagging scheduling conflicts. Decisions are faster and more data-driven. 3. Interview 3: AI enables evidence-backed decisions that keep projects on track with higher consistency. 4. Interview 4: Leadership uses AI dashboards to set the tone and promote fast, data-informed decisions. 5. Interview 5: AI analytics improved decision accuracy and consistency, reducing manual errors. 6. Interview 6: AI decision support reduces subjective errors and increases decision speed. 7. Interview 7: AI-based risk analysis prevents resource overcommitment and optimizes decisions. 8. Interview 8: Predictive analytics assists in faster, more accurate project decisions. 9. Interview 9: AI insights lead to	AI significantly improves decision accuracy, speed, and consistency in project management by correlating complex data on costs, risks, and timelines. Leadership increasingly relies on AI-driven dashboards and predictive analytics to make faster, evidence-based decisions that keep projects aligned with strategic goals and reduce idle time and manual errors.

					timely, consistent decision-making aligned with project goals. 10. Interview 10: Faster validated decisions reduce idle time and improve project delivery.	
3	Data Collection Accuracy	10	1,2,3,4,5,6,7,8,9,10	“data collection”, “logs”, “error reduction”	1. Interview 1: All project data is now captured through digital logs instead of manual sheets. Data duplication errors reduced by 80%. Documentation errors dropped significantly. 2. Interview 2: AI-based data collection tools and automated scheduling software improve accuracy and reduce manual efforts. 3. Interview 3: Field data capture via mobile AI apps reduced manual entry errors. Real-time validation catches anomalies. 4. Interview 4: AI helps standardize documentation and improves consistency. 5. Interview 5: Reliable data supports executive decisions through automated pipelines. 6. Interview 6: AI cross-verifies entries, greatly improving confidence in data accuracy. 7. Interview 7: Automated validation checks and data integrity tools boost reporting reliability. 8. Interview 8: Error margins decreased significantly with AI automation.	AI-driven automation of data capture and validation significantly minimizes manual entry errors, data duplication, and inconsistencies across project documentation. Real-time anomaly detection, digital logs, and automated pipelines build higher confidence in data integrity, enabling more reliable executive decision-making, planning, and reporting.

					9. Interview 9: Data collection systems reduce loss and mismatch risks. 10. Interview 10: Reporting accuracy improved for better planning and executive reviews.	
4	Enhancing Data Analysis	10	1,2,3,4,5,6,7,8,9,10	“analysis”, “predictive analytics”	1. Interview 1: AI helps understand project risk and cost patterns that manual analysis missed. It supports forecasting and risk planning. 2. Interview 2: Predictive analytics and data visualization tools support decision-making and project planning. 3. Interview 3: Complex risk and cost patterns are detected early; inefficiencies identified and addressed. 4. Interview 4: Forecast accuracy enables better planning and risk management. 5. Interview 5: Executives trust AI-driven forecasts for operational reviews. 6. Interview 6: Forecasts derived from AI tools are reliable and improve decision quality. 7. Interview 7: Forecasting models underpin risk and timeline management. 8. Interview 8: AI reveals inefficiencies and flags risks, aiding continuous improvement. 9. Interview 9: Analytics uncover hidden cost patterns and optimize resource use.	AI-driven predictive analytics and data visualization uncover complex risk and cost patterns often missed by manual analysis. These tools enable early detection of inefficiencies and risks, improve forecast accuracy, and support strategic resource optimization and operational adjustments. Executives increasingly trust AI-derived insights for planning and continuous improvement

					10. Interview 10: Data-backed insights drive strategic adjustments and operational efficiency.	
5	Risk Identification Accuracy	10	1,2,3,4,5,6,7,8,9,10	“risk”, “early warning”, “flag”	1. Interview 1: AI systems flag potential delay risks early. Early alerts help detect slow progress, allowing mitigation. 2. Interview 2: AI-generated risk maps guide mitigation planning and highlight vendor capacity risks. 3. Interview 3: AI predictive alerts prevent bottlenecks through early task reprioritization. 4. Interview 4: Workload-based bottleneck predictions enhance resource deployment. 5. Interview 5: Proactive mitigation steps based on AI insights refine risk culture. 6. Interview 6: Dynamic risk indicators enable agile project responses. 7. Interview 7: AI helps identify supplier delay risks and supports weekly risk mitigation. 8. Interview 8: Early risk identification has prevented major issues in procurement and scheduling. 9. Interview 9: System predictive alerts now prevent sudden surprises. 10. Interview 10: AI-driven risk culture	AI significantly improves risk identification accuracy by providing early predictive alerts, dynamic risk maps, and workload-based bottleneck forecasting. These capabilities enable proactive mitigation, prevent schedule and supply chain disruptions, and foster a data-driven risk culture that enhances project resilience and agility.

					fosters preventive actions and improves project resilience.	
6	Saving Time for Project Managers	10	1,2,3,4,5,6,7,8,9,10	“time”, “save hours”, “automation”	1. Interview 1: AI automation reduced time spent on reports and documentation, saving 8–10 hours weekly per manager. 2. Interview 2: AI tools balance cost against time saved, significantly improving efficiency. 3. Interview 3: Weekly updates auto-generated, reducing administrative burden and improving focus. 4. Interview 4: AI eliminated much manual tracking and sped coordination. 5. Interview 5: Automated report generation significantly cuts manual work. 6. Interview 6: More time now goes into strategic coordination and innovation. 7. Interview 7: AI tools save time spent on routine tasks and enable faster decision-making. 8. Interview 8: Time saved is reinvested in innovation and high-value tasks. 9. Interview 9: Communication delays decreased due to AI assistance. 10. Interview 10: Leadership leverages	AI automation significantly reduces the time managers spend on routine reporting, documentation, and manual tracking—saving up to 8–10 hours weekly per manager in some cases. By automating status updates, consolidating information, and streamlining communication, AI enables managers to focus more on strategic coordination and innovation, accelerating decision-making and improving overall project outcomes.

					saved time for strategic focus and better project outcomes.	
7	Enhancing Communication	10	1,2,3,4,5,6,7,8,9,10	“collaboration”, “dashboard”, “communication”	1. Interview 1: AI-enabled dashboards and communication platforms improve coordination between on-site and design teams, with automated meeting summaries. 2. Interview 2: AI tools summarize meeting discussions and action items, enhancing team alignment. 3. Interview 3: Virtual assistants and AI bots facilitate timely stakeholder engagement and clear data-driven communication. 4. Interview 4: Automated reporting and notifications reduce misunderstandings and keep teams synchronized. 5. Interview 5: Stakeholder meetings rely on AI summaries for focused discussions. 6. Interview 6: Team communication is fluid, with faster response times and fewer missed updates. 7. Interview 7: AI supports instant client updates and transparent project portals. 8. Interview 8: Automated meeting notes and integrated project feeds increase communication efficiency. 9. Interview 9: Clients appreciate quick	AI-powered communication platforms and dashboards streamline coordination between dispersed teams by automating meeting summaries, action item tracking, and status updates. These tools reduce communication delays, minimize misunderstandings, and promote transparent, real-time collaboration—building stronger trust among stakeholders and enabling more focused, data-driven project discussions.

					and transparent updates through AI-driven portals. 10. Interview 10: Reduced manual follow-ups and improved transparency have built stronger stakeholder trust.	
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The qualitative evidence indicates that participants experienced improvements across all seven project-management outcome dimensions. Project quality was associated with early error detection, automated inspection, traceability, and predictive monitoring. Decision-making was associated with faster, more consistent, and more evidence-based interpretation of cost, risk, and schedule information.

Data collection accuracy was linked to digital logs, automated validation, anomaly detection, and reduced manual entry. Data analysis was associated with predictive analytics, data visualization, early identification of cost and risk patterns, and improved forecasting.

Risk identification was described in terms of early alerts, risk maps, bottleneck prediction, supplier-risk monitoring, and proactive mitigation. Time efficiency was associated with automated reporting, documentation, status updates, and reduced administrative work. Communication improvements were linked to dashboards, meeting summaries, automated notifications, client portals, and faster stakeholder updates.

The universal presence of the seven outcome themes in the interviews provides qualitative support for the quantitative H3 finding that AI-PM is positively associated with all seven measured project-management outcomes.

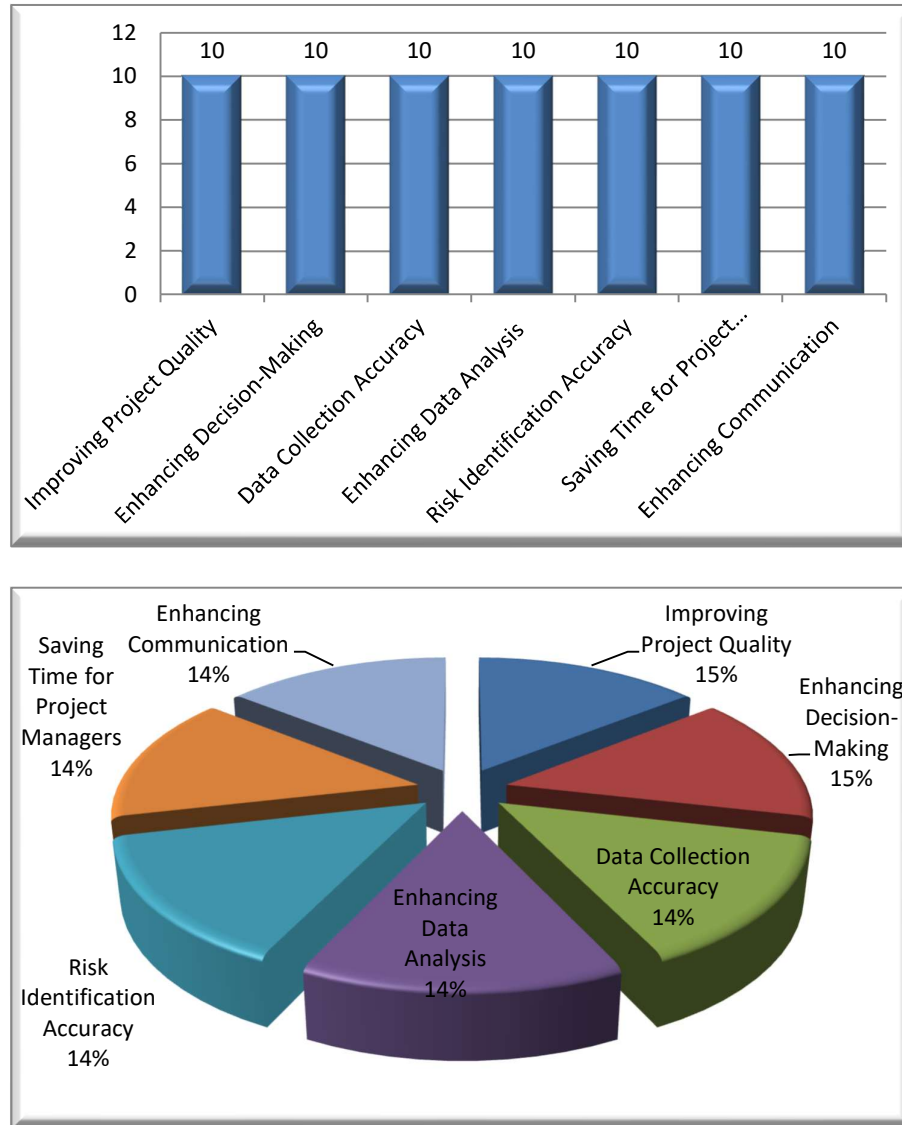


Figure (13): Frequency and Percentage of Dependent Variables (DVs)

The qualitative findings provide contextual evidence for the quantitative model. Organizational and technical conditions influence the feasibility and acceptance of AI-PM; AI-PM practices then operate through process automation, resource allocation, prioritization, reporting, and communication; and these practices are associated with improvements in decision-making, quality, data accuracy, analysis, risk identification, time efficiency, and collaboration. The qualitative evidence therefore supports the interpretation that AI-PM is not merely an additional technological tool. It is the practical mechanism through which organizational readiness can be translated into project-management improvements.

END OF APPENDIX C