

MIDOCEAN UNIVERSITY
College of Business Administration
Master of Business Administration

**THE IMPACT OF ARTIFICIAL INTELLIGENCE ON
CONSTRUCTION PROJECT PERFORMANCE AND
DECISION-MAKING EFFICIENCY**

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Academic Year: 2026

جامعة ميد أوشن
كلية إدارة الأعمال
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أثر الذكاء الاصطناعي على أداء مشاريع الإنشاءات وكفاءة اتخاذ القرار

رسالة ماجستير مقدمة إلى كلية إدارة الأعمال

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العام الأكاديمي: 2026

DEDICATION AND ACKNOWLEDGEMENTS

Dedication

I dedicate this thesis to my parents and family, whose support, patience, and encouragement have been a constant source of strength throughout my academic and professional journey. Their belief in the value of education and perseverance inspired me to complete this work with commitment and responsibility.

Acknowledgements

I would like to express my sincere appreciation to my supervisor, Dr. Alfaisal Hasan, for his guidance and academic support during the preparation of this research. I also extend my gratitude to MIDOCEAN University and the College of Business Administration for providing the academic framework for this study. Special thanks are due to the three reviewers who evaluated the questionnaire before distribution; their comments helped improve the clarity, relevance, and alignment of the final instrument. Finally, I thank all construction professionals who participated in the survey and generously shared their experience about artificial intelligence, project performance, and decision-making efficiency in Saudi construction projects.

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ABSTRACT

This study examines the relationships among artificial intelligence adoption, construction project performance, and decision-making efficiency among construction professionals in Saudi Arabia. A quantitative, cross-sectional survey design was used, and 123 valid responses were analyzed. The questionnaire was reviewed by three independent reviewers before distribution to strengthen face and content validity. The analysis included descriptive statistics, Cronbach's Alpha, Pearson correlation, simple and multiple regression, an exploratory indirect-effect test, and a one-sample t-test. Internal consistency was good to excellent across the four constructs ($\alpha = 0.855\text{--}0.928$; total-scale $\alpha = 0.960$). AI Adoption was strongly associated with Construction Project Performance ($r = 0.713$, $p < .001$) and Decision-Making Efficiency ($r = 0.772$, $p < .001$), while Decision-Making Efficiency was positively associated with Construction Project Performance ($r = 0.670$, $p < .001$). The combined regression model accounted for 54.3% of the variance in perceived project performance, and the exploratory indirect effect through decision-making efficiency was statistically significant. Respondents also agreed that AI should support engineers and project managers rather than replace them ($M = 4.195$, $p < .001$). Because the study is cross-sectional and perception-based, the findings indicate statistically significant associations rather than definitive causal effects. The study recommends phased implementation, stronger data governance, targeted workforce training, human oversight, and performance-based evaluation of AI use cases in Saudi construction organizations.

ARABIC ABSTRACT

تبحث هذه الدراسة في العلاقات بين تبني الذكاء الاصطناعي وأداء مشاريع الإنشاءات وكفاءة اتخاذ القرار لدى العاملين في قطاع الإنشاءات في المملكة العربية السعودية. اعتمدت الدراسة منهجاً كمياً مقطوعياً باستخدام استبانة إلكترونية، وتم تحليل 123 استجابة صالحة. راجع الاستبانة ثلاثة محكمين مستقلين قبل توزيعها لتعزيز الصدق الظاهري وصدق المحتوى. شملت التحليلات الإحصاءات الوصفية، ومعامل كرونباخ ألفا، وارتباط بيرسون، والانحدار البسيط والمتعدد، واختباراً استكشافياً للأثر غير وبلغ معامل الثبات، ($\alpha = 0.855-0.928$) المباشر، واختبار (ت) لعينة واحدة. أظهرت المقاييس اتساقاً داخلياً جيداً إلى ممتازاً وبين تبني، ($r = 0.713, p < .001$) الكلي 0.960. وجدت علاقة إيجابية قوية بين تبني الذكاء الاصطناعي وأداء المشاريع ($r = 0.670, p < .001$) كما ارتبطت كفاءة اتخاذ القرار إيجابياً بأداء المشاريع، ($r = 0.772, p < .001$) الذكاء الاصطناعي وكفاءة اتخاذ القرار وفسر نموذج الانحدار المشترك 54.3% من التباين في الأداء المدرك، وكان الأثر غير المباشر. ($0.670, p < .001$) الاستكشافي عبر كفاءة اتخاذ القرار دالاً إحصائياً. كذلك اتفق المشاركون على أن الذكاء الاصطناعي ينبغي أن يدعم المهندسين ونظراً للطبيعة المقطعية واعتماد البيانات على التصورات. ($M = 4.195, p < .001$) ومديري المشاريع لا أن يحل محلهم الذاتية، تعكس النتائج علاقات إحصائية ولا تثبت السببية بصورة قاطعة. وتوصي الدراسة بالتطبيق التدريجي، وتحسين حوكمة البيانات، وتدريب القوى العاملة، والإبقاء على الإشراف البشري، وقياس أثر حالات الاستخدام بمؤشرات أداء واضحة.

LIST OF ABBREVIATIONS

List of Abbreviations

Abbreviation	Meaning
AI	Artificial Intelligence
AIA	Artificial Intelligence Adoption
AIC	Artificial Intelligence Challenges
BIM	Building Information Modeling
CPP	Construction Project Performance
DME	Decision-Making Efficiency
HSE	Health, Safety, and Environment
IoT	Internet of Things
QA/QC	Quality Assurance / Quality Control
SPSS	Statistical Package for the Social Sciences
STS	Socio-Technical Systems

CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

The construction industry is a central contributor to economic and social development because it delivers the infrastructure required for housing, transportation, utilities, healthcare, education, commerce, tourism, and industrial activity. However, construction remains highly fragmented and information-intensive, which makes performance dependent not only on technical execution but also on the quality and timeliness of decisions across the project lifecycle (Darko et al., 2020; Abioye et al., 2021).

Construction projects frequently experience schedule delays, cost overruns, rework, quality nonconformance, safety incidents, inefficient resource use, fragmented information, and slow approvals. In real project settings, these issues can appear through late shop-drawing approvals, delayed inspection requests, utility-interface conflicts, incomplete method statements, late subcontractor mobilization, equipment breakdowns, material shortages, design changes, payment delays, and weak coordination between office and site teams. Recent construction-AI reviews indicate that these problems are among the reasons AI, digital twins, computer vision, and data-driven project controls are increasingly studied as decision-support tools for the built environment (Akinosho et al., 2020; Opoku et al., 2021; Pan & Zhang, 2021).

Artificial intelligence has become increasingly relevant to construction because it can process large datasets, identify patterns, forecast future outcomes, automate routine analytical tasks, interpret images and text, and support professional judgment. Literature on construction AI reports applications in delay prediction, cost forecasting, safety monitoring, progress tracking, document analysis, design coordination, and resource optimization (Fang et al., 2020; Wu et al., 2022; Adebayo et al., 2025).

The benefits of AI depend on the ability of construction professionals to convert information into action. An AI system may identify a potential delay, cost deviation, material shortage, quality issue, or safety risk, but project performance improves only when the information is understood, trusted, communicated, approved, and implemented. For this reason, decision-making efficiency is central to explaining the performance value of AI adoption (Holzmann et al., 2022; Song et al., 2025).

The Saudi context is relevant because Vision 2030 emphasizes digital transformation and large-scale development programs, while national data and AI initiatives promote data-driven

capabilities, responsible data use, and AI governance. In practical terms, this context includes large infrastructure, mixed-use, housing, tourism, and public-facility projects where teams must coordinate contractors, consultants, suppliers, design approvals, site inspections, and government requirements. This makes Saudi construction projects an appropriate context for examining whether AI adoption can improve project performance and decision-making efficiency.

1.2 Problem Statement

Construction projects operate in complex environments characterized by uncertainty, changing site conditions, multidisciplinary coordination, and significant financial, quality, and safety consequences. Although project organizations use schedules, cost reports, progress records, procurement logs, risk registers, quality documents, safety observations, BIM models, and monitoring systems, important decisions may still be delayed or based on incomplete, fragmented, or outdated information.

Traditional project-management practices often depend heavily on manual reporting, personal experience, and delayed feedback. These practices may be insufficient when project conditions change quickly or when information is distributed across different teams and systems. For example, a site team may discover that a required material has not arrived, a consultant may delay approval of a submittal, an RFI may remain unanswered while related work is already on the critical path, or a subcontractor may complete work that cannot be inspected because access, drawings, or testing documents are incomplete. Weak decision-making in such situations can lead to late corrective action, rework, inefficient resource allocation, unresolved technical issues, delayed material delivery, safety exposure, and weak performance.

AI offers potential solutions through predictive analytics, automated monitoring, risk identification, data integration, and decision support. However, AI adoption does not automatically improve project outcomes. Poor data quality, limited skills, resistance to change, weak management support, unclear governance, and lack of trust can reduce the value of AI-supported tools (Regona et al., 2022; Adebayo et al., 2025). Therefore, the key research problem is not only whether AI is available, but whether it improves project performance and supports efficient decisions across construction functions.

This study addresses the following main problem: construction organizations in Saudi Arabia need empirical evidence on whether AI adoption improves construction project performance and decision-making efficiency, and whether implementation challenges such as

skills, data quality, resistance to change, management support, privacy, and trust affect the practical value of AI-supported tools.

1.3 Significance of the Study

1.3.1 Theoretical Significance

The study contributes to the literature by linking AI adoption, decision-making efficiency, and construction project performance in one research framework. It also highlights human-AI collaboration rather than treating AI as a purely technical issue. The study recognizes that AI outputs require professional interpretation, communication, approval, implementation, and accountability.

1.3.2 Practical Significance

The study may help construction organizations understand where AI can add value beyond planning and cost control. The questionnaire covers site monitoring, procurement, material tracking, quality, safety, productivity, subcontractor monitoring, resources, and management decisions. This makes the findings useful to contractors, consultants, project managers, engineers, procurement teams, cost teams, QA/QC teams, and HSE teams.

1.3.3 Policy and Educational Significance

The study may support training programs that combine AI awareness with project management, data interpretation, decision-making, and ethical responsibility. It may also help academic institutions and professional bodies understand the type of AI skills needed in modern construction.

1.4 Research Objectives

General Objective: To examine the impact of artificial intelligence on construction project performance and decision-making efficiency among construction professionals in Saudi Arabia.

- Assess the perceived level of AI adoption and use in construction project planning, execution, monitoring, procurement, quality, safety, and management.
- Examine the perceived impact of AI on construction project performance indicators such as time, cost, quality, safety, productivity, resources, material availability, and subcontractor monitoring.

- Examine the perceived impact of AI on decision-making efficiency, including decision speed, accuracy, data analysis, alternative comparison, risk response, and problem solving.
- Identify key challenges affecting AI adoption in construction projects, including knowledge, resistance to change, data quality, management support, and ethical concerns.
- Examine whether AI is perceived as a supportive tool for engineers and project managers rather than a replacement for professional judgment.
- Provide practical recommendations for effective AI adoption in construction project management.

1.5 Research Questions

- How is AI perceived and adopted in construction projects by different professional groups?
- How does AI affect construction project performance across time, cost, quality, safety, productivity, resources, procurement, and site execution?
- How does AI affect decision-making efficiency in construction projects?
- What challenges may limit the effective use of AI in construction projects?
- Do construction professionals perceive AI as a support tool or as a replacement for engineers and project managers?
- What recommendations can improve the use of AI in construction project management?

1.6 Research Hypotheses

- H1: Artificial intelligence adoption has a statistically significant positive relationship with construction project performance.
- H2: Artificial intelligence adoption has a statistically significant positive relationship with decision-making efficiency.
- H3: Decision-making efficiency has a statistically significant positive relationship with construction project performance.
- H4: AI-related challenges have a statistically significant effect on the perceived effectiveness of AI adoption in construction projects.

- H5: Construction professionals significantly agree that AI supports engineers and project managers rather than fully replacing them.

Table 1.1 Study Variables and Roles

Variable	Role	Principal Dimensions
Artificial Intelligence Adoption	Independent variable	Planning, execution, monitoring, risk identification, reporting, coordination, data accuracy
Construction Project Performance	Dependent variable	Time, cost, quality, safety, productivity, resource allocation, procurement/material tracking, subcontractor monitoring
Decision-Making Efficiency	Dependent / mediating analytical variable	Speed, accuracy, data analysis, alternative comparison, risk response, problem solving, evidence-based decisions
Challenges of AI	Contextual factor	Knowledge, resistance, data quality, management support, privacy, human-AI relationship

Table 1.2 Alignment of Objectives, Questions, Hypotheses, and Questionnaire Sections

Objective	Research Question	Hypothesis	Questionnaire Items
AI adoption level	RQ1	Descriptive	Q7–Q14 and demographic AI questions
AI and performance	RQ2	H1	Q7–Q24
AI and decision-making efficiency	RQ3	H2	Q7–Q14 and Q25–Q34
DME and performance	RQ2/RQ3	H3	Q15–Q34
AI challenges	RQ4	H4	Q35–Q40 and Q42
AI support vs replacement	RQ5	H5	Q40 and Q43

1.7 Scope and Boundaries of the Study

- Subject boundary: The study focuses on AI applications in construction project management and their effect on project performance and decision-making efficiency. It does not study the technical programming of AI algorithms.
- Geographical boundary: The study focuses on construction projects in the Kingdom of Saudi Arabia.
- Temporal boundary: The primary data collection was conducted during 2026.
- Human boundary: The study includes construction professionals such as project managers, planning engineers, site engineers, construction engineers, procurement engineers, cost control engineers, QA/QC engineers, HSE engineers, consultants, contractors, and other project-related professionals.

- Unit of analysis: The individual construction professional is the unit of analysis. Each respondent provides one assessment based on current or recent experience in construction projects.

1.8 Definition of Key Terms

- Artificial Intelligence: Computer-based tools or systems that analyze data, identify patterns, forecast outcomes, automate activities, interpret images or text, identify risks, generate recommendations, or support project decisions.
- Construction Project Performance: The degree to which a construction project achieves performance targets related to time, cost, quality, safety, productivity, resources, materials, and project coordination.
- Decision-Making Efficiency: The ability of project professionals to make timely, accurate, evidence-based, and implementable decisions using available information and resources.
- AI Adoption: The extent to which AI-supported tools are used or accepted in project planning, execution, monitoring, reporting, risk identification, and coordination.
- Construction Professionals: Individuals involved in construction planning, execution, procurement, cost control, quality, safety, consultancy, contracting, or project management.

1.9 Chapter Summary

Chapter One introduced the study background, problem statement, significance, objectives, research questions, hypotheses, scope, and key definitions. It established that the research must not be limited to planning and cost control only, because construction project performance depends on decisions across multiple disciplines including site execution, procurement, quality, safety, resources, and project management.

CHAPTER TWO: LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

2.1 Introduction

This chapter reviews the literature related to artificial intelligence in construction projects, decision-making efficiency, and construction project performance. It also explains the theoretical foundation and the conceptual framework used in the study. The review focuses on recent sources and on the practical reality that AI value in construction depends on both technology and professional decision-making.

2.2 Artificial Intelligence in Construction Projects

AI refers to computational methods that can learn from data, recognize patterns, interpret images or language, forecast outcomes, optimize alternatives, automate processes, or support decisions. In construction, AI may be integrated with project-control systems, BIM, digital twins, drones, sensors, cloud platforms, document-management systems, and reporting tools.

AI applications in construction are broad. In planning, AI may support schedule forecasting, delay prediction, resource leveling, and early warning systems. In site execution, AI may support progress measurement, productivity analysis, equipment monitoring, safety-risk identification, and defect detection. In procurement, AI may support material availability tracking, supplier analysis, long-lead item monitoring, and delivery-risk forecasting. In quality and safety, AI may support inspection, nonconformance analysis, PPE monitoring, and hazard recognition.

Literature suggests that AI may improve forecasting, monitoring, reporting, decision support, safety, cost control, and resource efficiency. However, these potential benefits depend on data quality, user skills, organizational readiness, trust, governance, and the ability to act on AI outputs. Therefore, AI should be studied as part of a socio-technical system rather than as software alone.

Table 2.1 Principal AI Technologies and Construction Applications

Technology	Core Capability	Construction Applications
Machine learning	Learns patterns from historical or current data	Cost and duration prediction, productivity forecasting, risk classification
Deep learning	Models complex nonlinear relationships	Image recognition, defect detection, safety monitoring
Computer vision	Interprets images and video	Progress measurement, PPE detection, quality inspection
Natural language processing	Analyzes and summarizes text	Contract review, report summarization, document searching

Technology	Core Capability	Construction Applications
Expert / fuzzy systems	Applies rules under uncertainty	Risk evaluation, prioritization, compliance support
Optimization algorithms	Compares alternatives under constraints	Scheduling, resources, logistics, cost-time trade-offs
Generative AI	Generates text, summaries, alternatives, and explanations	Report drafting, knowledge access, document interrogation

2.3 Decision-Making Efficiency in Construction Projects

Decision-making is a continuous activity in construction projects. Professionals make decisions about design coordination, construction methods, procurement priorities, subcontractor performance, resources, cost, schedule, quality, safety, risk, and stakeholder requirements. These decisions are interdependent: a decision that accelerates progress may affect cost, quality, or safety.

Decision-making efficiency in this study means making decisions that are timely, accurate, informed, practical, and implementable. Speed alone is not enough because a fast decision may be wrong or unsafe. Similarly, an accurate decision may lose value if it is made too late. Efficient decision-making balances time, information, analysis, professional judgment, approval, implementation, and follow-up.

Research in project management and broader organizational settings indicates that AI can support decision-making by processing information, identifying patterns, forecasting risks, and assisting the comparison of alternatives. These findings are complementary rather than identical: Holzmann et al. (2022) examined project-management experts, whereas Song et al. (2025) studied technology acceptance and organizational decision-making in a general business-management context. In construction, final decisions still require professional judgment because they involve site conditions, contractual obligations, safety responsibility, ethics, stakeholder interests, and accountability.

2.4 Construction Project Performance

Construction project performance is multidimensional. Traditional performance measures focus on cost, time, and quality, but modern construction performance also includes safety, productivity, resource efficiency, stakeholder coordination, technology use, and sustainability.

This study therefore measures performance through a broad set of indicators suitable for different construction disciplines.

Cost performance concerns cost control, budget deviation, variation management, and the efficient use of financial resources. Time performance concerns progress, delay reduction, milestone achievement, and response to schedule deviations. Quality performance concerns compliance with specifications, reduction of defects, and control of rework. Safety performance concerns hazard identification, safe behaviors, incident prevention, and compliance. Resource and operational performance include manpower, material, equipment, productivity, and subcontractor monitoring.

2.5 Relationships Among the Study Variables

AI adoption can support project performance because AI can improve monitoring, prediction, risk identification, reporting accuracy, resource allocation, material tracking, quality control, and safety awareness. Decision-making efficiency is expected to improve when AI reduces uncertainty and provides faster access to evidence. Therefore, the study assumes that better AI adoption will be associated with better performance and more efficient decisions.

AI challenges may affect the usefulness of AI adoption. Poor data quality can produce unreliable outputs. Resistance to change may reduce use. Lack of management support may prevent implementation. Ethical and privacy concerns may limit data sharing. For these reasons, the study includes challenges as a contextual factor that must be understood when interpreting AI adoption and project outcomes.

2.6 Previous Studies and Critical Analysis

Recent studies show increasing interest in AI-enabled construction and project management. However, many studies focus on technical applications or literature reviews rather than primary evidence from multidisciplinary professionals in one national construction context. The current study responds by collecting survey data from construction professionals in Saudi Arabia and testing relationships among AI adoption, decision-making efficiency, project performance, and AI challenges.

2.7 Theoretical Framework

The study is guided by a socio-technical systems perspective, technology acceptance logic, and decision-support thinking. The socio-technical perspective explains that technology creates

value only when integrated with people, workflows, organizational structure, data quality, and governance. AI therefore cannot be evaluated only as software; it must be examined as part of a project system involving engineers, project managers, site teams, cost teams, quality teams, safety teams, suppliers, and decision authorities.

Technology acceptance logic explains that professionals are more likely to adopt tools when they perceive them as useful, understandable, and relevant to their work. Decision-support thinking explains how information systems improve managerial decisions by organizing data, comparing alternatives, forecasting outcomes, and reducing uncertainty. Together, these foundations support the study's focus on AI adoption, decision-making efficiency, and construction project performance.

2.8 Conceptual Framework and Model Development

The conceptual framework assumes that AI adoption influences construction project performance and decision-making efficiency. It also assumes that decision-making efficiency is associated with construction project performance because better decisions support better time, cost, quality, safety, resource, procurement, and site outcomes. AI challenges are included as implementation considerations that may affect the successful use of AI in construction projects.

Table 2.2 Conceptual Framework of the Study: AI Adoption, Decision-Making Efficiency, Project Performance, and Implementation Challenges

AI Adoption	→	Decision-Making Efficiency
↓		↓
Construction Project Performance	←	AI Challenges / Implementation Context

2.9 Research Gap and Contribution of the Current Study

Table 2.2 summarizes the main research gaps identified from the reviewed literature and explains how the current study responds to each gap. This table strengthens the alignment between the literature review, the questionnaire design, and the statistical analysis by showing that the study does not only repeat previous research but addresses a contextual and methodological need in Saudi construction projects.

Table 2.3 Research Gaps and Current Study Response

Gap	Limitation in Existing Literature	Current Study Response
Theoretical	AI is often treated independently from people and work processes.	Applies a socio-technical explanation integrating AI, professional decisions, and performance.
Decision mechanism	Decision-making is described as a benefit but rarely tested as a distinct outcome.	Measures decision-making efficiency as a main variable linked to AI adoption.
Empirical	Many studies are reviews or technical algorithm evaluations.	Collects primary quantitative data from construction professionals.
Contextual	Limited integrated evidence from Saudi construction projects.	Tests the complete model in Saudi Arabia.
Measurement	Performance is often narrowly measured.	Uses multidimensional measures for AI, DME, CPP, and AI challenges.
Population	Some studies focus on one discipline or department.	Includes multiple engineering and project-related professions.

2.10 Expanded Functional Review of AI Applications in Construction

The following expanded review organizes AI applications by construction function. This structure was added because construction project performance is multidisciplinary, and AI may affect each performance dimension through different mechanisms. The purpose is to make the literature review more comprehensive and to clarify how AI can contribute to planning, cost, procurement, quality, safety, document control, BIM coordination, and human decision-making.

2.10.1 AI in Planning, Scheduling, and Progress Forecasting

AI applications in planning and scheduling are particularly relevant because construction projects are time-sensitive systems in which many activities depend on predecessor logic, procurement readiness, resource availability, site access, and approval cycles. Traditional planning tools can represent sequence and duration, but they depend heavily on human interpretation and manual updates. AI-supported planning can add value by analyzing large volumes of historical and real-time information, identifying patterns in delay causes, predicting future slippage, and suggesting corrective actions before the delay becomes critical.

In the context of this study, planning-related AI is not limited to automated schedule generation. It includes predictive alerts for late material delivery, risk-based look-ahead planning, labor-productivity forecasting, progress-photo interpretation, and automated comparison between planned and actual progress. For example, if façade installation is delayed because shop drawings, mock-up approval, and material delivery are not aligned, an AI-supported system could flag the combined risk earlier than a traditional weekly report. This broader view is important because a

construction schedule is affected by design decisions, procurement cycles, subcontractor performance, quality approvals, safety constraints, and site logistics. Therefore, the relationship between AI adoption and project performance should be interpreted as a multidisciplinary relationship rather than a narrow scheduling issue.

2.10.2 AI in Cost Control, Procurement, and Resource Optimization

Cost performance in construction is affected by quantity growth, productivity loss, rework, material escalation, change orders, subcontractor claims, equipment utilization, late procurement decisions, and delayed payment cycles. On active projects, cost pressure may also increase when crews wait for access, equipment is idle because preceding work is incomplete, or urgent procurement is required after a missed planning milestone. AI-supported cost control can assist project teams by identifying abnormal cost trends, comparing actual cost against budgeted cost, forecasting final cost, and highlighting activities or packages that require management attention. This improves the quality of cost-related decisions because project teams can act based on early indicators rather than delayed monthly reports.

Procurement is also a major area where AI may support decision-making efficiency. Long-lead materials, vendor evaluation, purchase-order tracking, submittal approval, delivery risks, customs clearance, storage constraints, and material availability affect site execution. In a building project, for instance, delayed elevators, façade panels, chillers, fire-fighting pumps, waterproofing materials, or electrical switchgear can stop several downstream activities even when site labor is available. AI can help construction organizations prioritize procurement risks, classify vendor documents, detect missing information, and estimate the impact of late procurement on schedule and cost. For Saudi construction projects, where large infrastructure and mixed-use projects often involve complex supply chains, procurement-related AI can contribute directly to time, cost, and resource performance.

2.10.3 AI in Quality, Safety, and Site Monitoring

Quality and safety are among the most important performance dimensions in construction because they affect cost, schedule, reputation, and worker wellbeing. AI-supported computer vision can be used with cameras, drones, images, and videos to identify unsafe behaviors, missing personal protective equipment, workface congestion, progress deviations, or visible defects. For example, image-based monitoring may help identify workers entering restricted areas, missing helmets, unsafe scaffolding conditions, unsafe lifting zones, poor housekeeping, repeated concrete

surface defects, water leakage, damaged finishes, or incomplete installation work before these issues become larger project problems. These applications do not remove the need for safety officers, engineers, or inspectors. Rather, they can increase the frequency and consistency of monitoring by providing additional information for human review.

Quality-related AI may also assist with defect classification, inspection records, nonconformance trends, document review, and lessons learned. When quality issues are detected early, project teams can reduce rework and improve compliance with specifications. However, AI outputs must be verified within the technical and contractual context of the project. This supports the human-AI collaboration position adopted in this thesis: AI can strengthen professional judgment by improving information availability, but accountability and final decisions remain with competent professionals and management systems.

2.10.4 AI, BIM, Document Control, and Information Integration

Modern construction projects generate large volumes of data through schedules, BIM models, drawings, RFIs, submittals, inspection requests, daily reports, progress photos, cost reports, procurement logs, and risk registers. One reason decision-making becomes inefficient is that these data sources may be fragmented across different platforms and departments. A project manager may need to check the latest drawing revision, the related RFI response, the approved material submittal, and the inspection status before approving a site decision. AI can support information integration by classifying documents, extracting key information, detecting inconsistencies, and summarizing project information for decision-makers.

BIM-related AI has the potential to improve design coordination, clash prioritization, quantity extraction, progress verification, and handover documentation. Natural-language processing can support the review of RFIs, contracts, meeting minutes, and technical correspondence. In practice, this can help when mechanical, electrical, plumbing, structural, and architectural teams issue different drawing revisions, when a clash is discovered after procurement has started, or when repeated site instructions create confusion about the approved scope. These applications are important for this research because decision-making efficiency depends not only on speed but also on the accuracy, completeness, and accessibility of project information. If AI improves the reliability of project information, it may indirectly improve construction project performance through better decisions.

2.10.5 Human-AI Collaboration in Construction Projects

Literature increasingly emphasizes that AI should be understood as a socio-technical tool rather than a fully independent replacement for professional expertise. Construction decisions require interpretation of site conditions, contractual obligations, design intent, stakeholder expectations, safety responsibilities, and practical constraints. AI can process data faster than humans in specific tasks, but it may not understand organizational priorities, legal responsibility, ethical trade-offs, or site-specific limitations in the same way as experienced professionals.

For this reason, the current study includes a specific research question and hypothesis regarding whether AI is perceived as a supportive tool rather than a replacement for engineers and project managers. This is not only an ethical issue but also a performance issue. If professionals perceive AI as a threat, adoption may be resisted. If they perceive it as a decision-support tool, they are more likely to use it responsibly and integrate it into daily project-management processes.

2.10.6 Implementation Challenges and Readiness Requirements

AI adoption in construction faces several barriers, including limited technical knowledge, inconsistent data quality, fragmented digital systems, resistance to change, unclear governance, cybersecurity concerns, and lack of management support. These challenges are especially important because AI systems depend on reliable data. If input data are incomplete, outdated, or biased, the resulting recommendations may mislead decision-makers rather than support them.

Implementation readiness requires more than purchasing software. It requires clear objectives, trained users, data standards, governance rules, privacy controls, pilot testing, and performance measurement. Project teams also need practical procedures for data ownership, daily data entry, model updating, document naming, dashboard review, issue escalation, and corrective-action tracking. Without these routines, AI tools may become another reporting layer rather than a real decision-support system. The survey instrument therefore included an AI Challenges construct to examine whether respondents perceive knowledge, resistance, data quality, management support, privacy, and the human-support role of AI as relevant implementation considerations.

Table 2.4 Expanded AI Applications across Construction Project Functions

Project Function	AI Applications	Expected Contribution to Performance	Human Oversight Requirement
Planning and scheduling	Delay prediction, look-ahead risk alerts, progress forecasting	Earlier corrective action and improved schedule control	Planner validates logic, constraints, and recovery plan
Cost control	Cost trend detection, estimate forecasting, variance explanation	Improved cost awareness and budget control	Cost team validates assumptions and contract implications
Procurement	Vendor-document classification, material delay alerts, long-lead tracking	Reduced procurement surprises and stronger material availability	Procurement team evaluates suppliers and commercial decisions
Quality management	Defect recognition, nonconformance trend analysis, inspection support	Lower rework and stronger compliance with specifications	QA/QC team confirms technical acceptability
Safety management	Computer-vision monitoring, hazard pattern detection, safety observations	Better risk identification and faster safety interventions	HSE team confirms hazards and corrective actions
Document control and reporting	RFI/submittal classification, report summarization, correspondence analysis	Faster information retrieval and improved decision evidence	Project team reviews accuracy and confidentiality
BIM and coordination	Clash prioritization, quantity support, progress comparison	Improved coordination and reduced design-related disruption	Design and construction teams validate constructability

Table 2.4 expands the literature review by linking AI applications to project functions, expected performance contributions, and the required human oversight. The table reinforces the study position that AI can support multiple construction functions, but its value depends on professional validation, governance, and integration into project workflows.

2.11 Critical Synthesis of Previous Studies

A critical synthesis of the reviewed studies shows that the value of AI in construction is not limited to one technical application. Research on AI in construction generally falls into several streams: predictive analytics, computer vision, automation, digital project management, decision support, adoption challenges, and human-AI collaboration. Each stream contributes to the present study, but each also leaves limitations that justify the current empirical survey.

Studies focusing on predictive analytics show that AI can improve forecasting and early warning. However, forecasting alone does not improve performance unless project teams are able to interpret the warning and implement corrective action. For example, a model may predict a two-week delay in structural works, but the benefit depends on whether the project team can identify the cause, approve overtime or resequencing, coordinate subcontractors, and communicate the

recovery plan. This supports the inclusion of Decision-Making Efficiency as a key variable in the current research. AI may provide useful signals, but the benefit depends on whether decisions become faster, more accurate, and better followed up.

Studies focusing on computer vision and automation demonstrate that AI can support site monitoring, quality inspection, and safety observation. Their limitation is that many are technical demonstrations or pilot applications. They may show that the algorithm can detect an object, defect, or unsafe behavior, but they do not always explain how this information is used by project managers, engineers, contractors, or consultants to improve project performance at the organizational level. In practice, a detected safety violation must still be investigated, assigned to a responsible person, recorded, corrected, and followed up through the site safety system.

Studies on digital project management and AI-enabled project-management tools often highlight improved reporting, decision support, and risk management. However, they may focus on general project management rather than the construction environment specifically. Construction has unique characteristics, such as temporary project organizations, subcontracting, site variability, physical progress constraints, regulatory approvals, technical inspections, utility interfaces, access limitations, permit requirements, weather exposure, and contractual claims. These characteristics make construction a distinct context for AI adoption.

Adoption-focused studies emphasize barriers such as knowledge gaps, resistance to change, poor data quality, lack of management support, and ethical concerns. These barriers are central to the current study because technology may be technically powerful but practically ineffective if organizations are not ready to use it. Therefore, the thesis measures AI Challenges as a separate construct rather than assuming that AI adoption automatically creates value.

Finally, the reviewed studies support the argument that AI should complement human expertise. The role of engineers and project managers remains important because construction decisions involve technical judgment, coordination, accountability, safety responsibility, and stakeholder negotiation. This reinforces the research question on whether AI supports or replaces engineers and justifies including a direct item and an open-ended question on this issue.

Table 2.5 Critical Literature Synthesis by Theme

Literature Theme	What the Literature Shows	Limitation in Prior Studies	How the Current Study Responds
Predictive analytics	AI can forecast delay, cost trends, risk events, and productivity patterns.	Many studies focus on prediction accuracy rather than organizational decision use.	Tests how AI Adoption relates to Decision-Making Efficiency and Performance.

Table 2.5 demonstrates how the literature review was converted into the empirical design of the study. Each limitation in previous research is connected to a measurement decision in the current questionnaire, which strengthens the alignment between the literature review, the research gap, and the statistical analysis.

2.12 Integrated and Paraphrased Literature Update

Broad reviews of AI in construction indicate that the field has moved from isolated algorithm development toward applied use cases in planning, monitoring, safety, quality, cost, resources, and management decision support (Darko et al., 2020; Akinosho et al., 2020; Abioye et al., 2021; Pan & Zhang, 2021). These studies support the current thesis because they show that AI is relevant to several project-performance dimensions rather than one technical function only. In practical construction terms, this means the study considers AI not only as a scheduling tool, but also as support for site reporting, inspection follow-up, procurement tracking, cost warning, and coordination between office and site teams.

AI adoption in construction is not limited to predictive scheduling or cost control. Research on computer vision and deep learning shows that AI can support safety observation, image-based activity recognition, progress monitoring, and site-condition interpretation; however, these benefits depend on data availability, model reliability, and practical integration with site workflows (Fang et al., 2020; Guo et al., 2021; Rehman et al., 2022). This supports the questionnaire design because the survey measures performance across time, cost, quality, safety, productivity, resources, materials, and subcontractor monitoring.

Text-based AI applications are increasingly relevant because construction projects produce large volumes of reports, drawings, contracts, submittals, RFIs, correspondence, and inspection records. Research on natural language processing shows that unstructured construction text can be organized, searched, and analyzed to support information exchange and downstream management decisions. Broader reviews of AI-enabled project management also identify document analysis and

knowledge support as developing applications that require validation, governance, and human oversight (Wu et al., 2022; Taboada et al., 2023; Adebayo et al., 2025).

Digital twin research is important because it links real-time data, simulation, monitoring, and forecasting. In construction, digital twins can support progress control and lifecycle decision-making, but their effectiveness depends on data integration, interoperability, organizational readiness, and clear performance metrics (Opoku et al., 2021). This reinforces the present study's view that AI value is created through a socio-technical system rather than through technology alone.

Project-management research indicates that AI may enhance planning, forecasting, reporting, risk analysis, communication, and decision-making, but it also changes expectations for project managers and teams. Studies in AI-enabled project management stress that AI can improve efficiency and information quality, while the human role remains central in interpreting outputs, managing stakeholders, and making accountable decisions (Holzmann et al., 2022; Taboada et al., 2023; Project Management Institute, 2024; Salimimoghadam et al., 2025).

Adoption challenges are repeatedly emphasized in the literature. Resistance to change, limited skills, weak data quality, fragmented systems, uncertain return on investment, ethical concerns, privacy, and trust can reduce the practical value of AI adoption. These themes directly informed the AI Challenges construct used in the questionnaire (Regona et al., 2022; Emaminejad & Akhavian, 2022; Liang et al., 2023; Saudi Data & AI Authority, 2023).

The Saudi context gives the study additional relevance. Vision 2030 highlights digital transformation and major development programs, while the national data and AI agenda emphasizes the importance of data-driven capabilities. Therefore, AI adoption in Saudi construction should be examined as both a technology issue and a project-performance issue linked to national transformation, governance, and professional capability (Saudi Vision 2030, 2025; Saudi Data & AI Authority, 2020).

The empirical model in this thesis is also consistent with recent technology-acceptance research. AI adoption is more likely to influence performance when professionals perceive the technology as useful and when organizational conditions support its application. The focus on decision-making efficiency is therefore appropriate because decision speed, accuracy, alternative comparison, risk response, and evidence-based problem solving represent the mechanism through which AI outputs become project actions (Song et al., 2025).

Chapter Two uses these sources as synthesized support for the research model. Rather than describing AI benefits in general terms only, the review connects the literature to practical construction situations such as delayed approvals, material tracking, site inspections, safety observations, drawing coordination, subcontractor performance, utility-interface problems, access constraints, cost variation, and project reporting. This approach supports academic integrity while still acknowledging the contribution of previous studies through APA-style citations.

Table 2.6 Integrated Reference Use and Paraphrased Evidence

Reference Group	How it is Used in the Thesis	Paraphrased Implication for the Current Study
AI in construction reviews	Darko et al. (2020); Akinosho et al. (2020); Abioye et al. (2021); Pan and Zhang (2021); Adebayo et al. (2025)	AI applications cover many construction functions, so the thesis measures performance broadly rather than limiting the topic to planning only.
Safety, vision, and progress monitoring	Fang et al. (2020); Guo et al. (2021); Rehman et al. (2022)	Computer vision and automated monitoring may support safety and progress control, but human validation remains necessary.
Digital twins and data integration	Opoku et al. (2021)	Digital twin value depends on real-time data quality, interoperability, and decision-oriented use.
AI-enabled project management	Holzmann et al. (2022); Taboada et al. (2023); PMI (2024); Salimimoghadam et al. (2025)	AI may improve planning and decision support, while project managers remain responsible for judgment and stakeholder coordination.
Adoption barriers and ethics	Regona et al. (2022); Emaminejad and Akhavian (2022); SDAIA (2023)	Trust, privacy, ethics, skills, resistance, and data governance are implementation requirements, not secondary issues.
Methodology and research ethics	Saunders et al. (2019); Wang and Cheng (2020); Yusof et al. (2022)	The quantitative cross-sectional design and questionnaire process require transparent reporting, informed participation, and cautious interpretation.
Saudi context	Saudi Vision 2030 (2025); SDAIA (2020)	The Saudi construction environment is suitable for studying AI because national transformation increasingly depends on digital and data-driven capabilities.

2.13 Chapter Summary

Chapter Two reviewed AI applications and barriers, defined decision-making efficiency, established a multidimensional performance construct, analyzed previous studies, adopted a socio-technical framework, and developed the conceptual model. The review connected AI adoption to real construction challenges such as delayed approvals, procurement risks, fragmented project

information, subcontractor coordination, safety observations, inspection delays, utility interfaces, rework, and cost variation. It identified a need for primary Saudi evidence testing the relationship among AI adoption, decision-making efficiency, construction project performance, and AI challenges.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes the methodological procedures used to answer the research questions and test the hypotheses. It explains the research design, target population, sampling approach, questionnaire development, validity and reliability procedures, data collection, coding, statistical analysis, ethical safeguards, and methodological limitations.

3.2 Research Design

The study employed a quantitative descriptive-analytical design. The descriptive component summarizes respondents' professional characteristics and their levels of agreement with the questionnaire statements. The analytical component examines statistical relationships among Artificial Intelligence Adoption (AIA), Construction Project Performance (CPP), Decision-Making Efficiency (DME), and AI-related implementation considerations (AIC). Because the study is based on cross-sectional survey perceptions, the analysis focuses on relationships, associations, and predictive patterns within the observed data rather than confirmed real-world causal effects.

The design was cross-sectional and non-experimental: data were collected once, and no variable was manipulated by the researcher. The questionnaire was administered through Google Forms, exported to Excel, coded numerically, and analyzed using procedures that can be reproduced in SPSS. Accordingly, the results describe associations and predictive relationships within the survey data; they do not establish temporal or causal effects.

Table 3.1 Summary of Research Design

Element	Description
Research approach	Quantitative
Research design	Descriptive analytical, cross-sectional survey
Data-collection tool	Structured Google Forms questionnaire
Main scale	Five-point Likert scale
Sampling technique	Non-probability purposive sampling with professional-referral support
Final valid sample	123 construction professionals
Key analyses	Frequencies, descriptive statistics, reliability, correlation, regression, hypothesis testing

3.3 Study Population and Sample

The target population comprised professionals working in or closely connected with construction projects in Saudi Arabia. The study was intentionally multidisciplinary and included project managers, planning engineers, site and construction engineers, procurement and cost-control professionals, QA/QC and HSE personnel, consultants, contractors, and other project-control or management roles.

The final analytical dataset contained 123 valid responses. Participants were reached through purposive professional distribution supported by referrals within construction networks. Because the questionnaire link was circulated through several channels and the total number of recipients was not known, a conventional response rate could not be calculated. The sample was sufficient for the descriptive, reliability, correlation, and regression procedures reported in this thesis, but its non-probability composition limits statistical generalization to the entire Saudi construction workforce. Therefore, the findings should be understood as supporting exploratory and statistical testing within the sampled respondents rather than as population-wide estimates.

3.4 Questionnaire Design and Measurement

The questionnaire was developed from the research objectives, questions, hypotheses, and conceptual framework. It contained six demographic and professional questions, 34 closed statements, and three open-ended questions. Closed statements used a five-point Likert scale coded as 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree. Composite scores were calculated as item means so that every construct remained on the original 1-to-5 scale.

Table 3.2 Questionnaire Structure

Section	Content	Items / Questions
Section A	Demographic and professional information	Q1–Q6
Section B	Artificial Intelligence Adoption	Q7–Q14
Section C	Construction Project Performance	Q15–Q24
Section D	Decision-Making Efficiency	Q25–Q34
Section E	AI Challenges and human-AI relationship	Q35–Q40
Section F	Open-ended questions	Q41–Q43

3.5 Validity and Reliability Procedures

Face and content validity were addressed before data collection. Three independent reviewers with relevant academic and construction/project-management experience assessed the clarity, wording, relevance, response scale, and alignment of the instrument with the research objectives and variables. Their comments were used to refine ambiguous wording and improve item alignment. After data collection, internal consistency was assessed with Cronbach's Alpha for each construct. These procedures support face validity, content validity, and reliability; however, no exploratory or confirmatory factor analysis was conducted, so the underlying factor structure should be treated as a limitation rather than assumed to be fully established (Saunders et al., 2019; Wang & Cheng, 2020).

Table 3.3 Operationalization of Study Variables

Variable	Operational Definition	Measurement Items
AI Adoption	Perceived use and usefulness of AI in planning, monitoring, reporting, risk identification, coordination, and project data.	Q7–Q14
Construction Project Performance	Perceived contribution of AI to time, cost, quality, safety, productivity, resources, procurement, and subcontractor monitoring.	Q15–Q24
Decision-Making Efficiency	Perceived contribution of AI to decision speed, accuracy, evidence, alternatives, risk response, and problem solving.	Q25–Q34
AI Challenges	Perceived barriers, ethical issues, readiness conditions, and human-AI role considerations related to AI implementation.	Q35–Q40

3.6 Data-Collection Procedures

Data were collected through an electronic questionnaire distributed to construction professionals working in or connected with projects in Saudi Arabia. The introductory statement explained the academic purpose of the study and the voluntary nature of participation. The instrument did not request names, national identification numbers, employee numbers, or confidential project information. Responses were reported only in aggregate form.

3.7 Data Preparation and Coding

The exported Google Forms file was checked for row structure, missing values, coding consistency, and valid scale ranges. The header row was excluded, leaving 123 respondent records. Likert responses were coded from 1 to 5, and each construct score was calculated as the mean of its designated items. The items Q35–Q40 were retained as the original AIC composite for

consistency with the questionnaire and reported analysis. Because Q40 is positively worded and measures the preferred human-AI relationship rather than a barrier, the AIC score is interpreted as a broad set of implementation considerations, not as a purely negative barrier-severity scale. This interpretation should also guide the discussion of AIC results in Chapters Four and Five. Q40 was therefore also tested separately. Open-ended answers were thematically grouped to support interpretation and were not used as predictors in the formal hypothesis tests.

3.8 Statistical Data-Analysis Plan

Table 3.4 Planned and Applied Statistical Analysis

Analysis	Purpose	Variables / Data
Frequencies and percentages	Describe respondent profile	Demographic questions Q1–Q6
Descriptive statistics	Measure general level of agreement	AIA, CPP, DME, AIC composite means
Cronbach's Alpha	Assess internal consistency	AIA, CPP, DME, AIC and total scale
Pearson correlation	Test strength and direction of relationships	AIA, CPP, DME, AIC
Regression analysis	Test predictive relationships within the survey data and support hypothesis testing	AIA and DME jointly predicting CPP; exploratory indirect-effect calculation
One-sample test	Test agreement with supportive-role item	Q40 human-AI support item compared with neutral value 3
Open-ended thematic summary	Support interpretation of quantitative results	Q41–Q43

3.9 Ethical Considerations

The study followed the principles of voluntary participation, informed consent, anonymity, confidentiality, and academic integrity. Respondents could choose whether to participate and were not asked for identifying or commercially sensitive information. Data were used only for academic analysis and were summarized at group level. The treatment of privacy, access, and responsible AI use was aligned with the general principles of Saudi data-protection and data-governance guidance (Saudi Data & AI Authority, 2023; Yusof et al., 2022).

3.10 Methodological Limitations

- The cross-sectional design captures perceptions at one point in time and cannot establish temporal order or causality.

- Purposive, referral-supported sampling and the absence of a known distribution denominator limit representativeness and prevent calculation of a conventional response rate.
- All principal variables were measured through the same self-report questionnaire, creating possible common-method and social-desirability bias.
- The study relied on perceived performance rather than audited schedule, cost, quality, safety, or productivity records.
- Construct validity was not tested through exploratory or confirmatory factor analysis, and the AIC composite includes a conceptually distinct human-AI role item.

3.11 Data-Analysis Procedures and Decision Rules

This section specifies how the questionnaire data were converted into analytical variables and how each statistical result was interpreted. The purpose is to provide a transparent link between the instrument, the hypotheses, and the findings reported in Chapter Four.

3.11.1 Rationale for the Statistical Analysis Procedures

Frequencies and percentages were used for demographic variables. Means and standard deviations summarized Likert items and composite construct scores. Cronbach's Alpha assessed internal consistency, with construct-specific coefficients treated as more informative than the total-scale coefficient because the questionnaire measures several conceptually distinct dimensions.

Pearson correlation quantified the direction and strength of bivariate associations. Simple linear regressions tested the predictive relationships specified in H1–H4, while a multiple regression assessed the simultaneous contribution of AIA and DME to CPP. A Sobel test was reported as an exploratory assessment of the indirect path from AIA to CPP through DME. Because the study is cross-sectional and did not use bootstrapped confidence intervals or a full structural model, the indirect-effect result is treated as supplementary evidence and not as definitive proof of causal mediation.

3.11.2 Data-Quality and Construct-Scoring Procedures

All closed responses were required in the electronic form, and the resulting Q7–Q40 dataset contained no missing values. Composite means were calculated only after checking that each

response fell within the valid 1-to-5 range. Averaging rather than summing preserved the original scale and allowed constructs with different numbers of items to be compared directly.

The four reported composites were AIA, CPP, DME, and AIC. AIA, CPP, and DME represent coherent directional constructs. The AIC composite combines five barrier-oriented statements with one human-AI role statement; consequently, higher AIC scores indicate stronger recognition of implementation considerations as a group and should not be interpreted automatically as greater resistance or a more negative adoption environment. Chapters Four and Five should therefore interpret AIC findings as implementation-context evidence rather than as a purely negative challenge index.

3.11.3 Interpretation Rules Used in the Analysis

Mean scores were interpreted using five equal-width categories: 1.00–1.79 = very low, 1.80–2.59 = low, 2.60–3.39 = moderate, 3.40–4.19 = high, and 4.20–5.00 = very high. Statistical significance was assessed at $\alpha = .05$. Cronbach's Alpha values of .70 or above were considered acceptable, values above .80 good, and values above .90 excellent. Correlation coefficients were interpreted by their magnitude and practical context rather than by rigid labels alone.

Regression coefficients and R^2 values were interpreted as predictive relationships within the observed survey scores. No claim is made that AI adoption physically caused verified changes in schedule, cost, quality, safety, or productivity. The absence of longitudinal data, objective project records, and full diagnostic or factor-analysis evidence requires cautious interpretation. Therefore, terms such as relationship, association, perceived effect, and predictive relationship within the survey data are preferred when discussing the results.

Table 3.5 Detailed Measurement and Analysis Matrix

Construct / Variable	Questionnaire Items	Score Calculation	Main Tests Applied	Purpose in the Study
AI Adoption	Q7-Q14	Average of eight Likert items	Descriptives, reliability, correlation, regression	Independent variable measuring perceived AI use and capability
Construction Project Performance	Q15-Q24	Average of ten Likert items	Descriptives, reliability, correlation, regression	Dependent variable measuring perceived performance outcomes
Decision-Making Efficiency	Q25-Q34	Average of ten Likert items	Descriptives, reliability, correlation, regression, mediation support	Mediating variable explaining how AI may improve performance

Construct / Variable	Questionnaire Items	Score Calculation	Main Tests Applied	Purpose in the Study
AI Challenges / Implementation Considerations	Q35-Q40	Average of six Likert items	Descriptives, reliability, correlation, regression	Mixed implementation construct; Q40 also analyzed separately
Open-ended responses	Q41-Q43	Thematic summary	Qualitative support	Practical explanation of benefits, barriers, and human-AI relationship

Table 3.5 summarizes the operational link among questionnaire items, composite scores, statistical tests, and the role of each variable. It also clarifies that the human-AI support item was retained within the original AIC composite but analyzed separately for H5.

3.12 Chapter Summary

Chapter Three presented the quantitative cross-sectional methodology, multidisciplinary target population, purposive sampling approach, questionnaire design, validity and reliability procedures, coding rules, statistical tests, ethical safeguards, and limitations. The next chapter reports the empirical results while preserving the distinction between statistical association and causal inference.

CHAPTER FOUR: RESULTS AND ANALYSIS

4.1 Introduction

This chapter reports the empirical findings from the 123 valid questionnaires. It presents data screening, respondent characteristics, internal consistency, construct and item descriptives, correlations, regression-based hypothesis tests, an exploratory indirect-effect analysis, the human-AI support test, and a thematic summary of the open-ended responses.

4.2 Usable Responses and Data Screening

The exported spreadsheet contained one header row and 123 respondent rows. After excluding the header, all 123 records were retained. The required Likert items Q7–Q40 contained no missing values and all values fell within the valid range of 1–5. Open-ended questions contained voluntary non-responses; these did not affect the quantitative analyses.

Composite scores were calculated as the mean of the designated items for AIA, CPP, DME, and AIC. No cases were excluded. The screening process established completeness and valid coding for the quantitative dataset. However, the available outputs did not provide a full assessment of distributional shape, influential cases, multicollinearity diagnostics, or residual assumptions. For this reason, the regression findings are interpreted as predictive relationships within the survey data rather than as confirmed causal effects.

Table 4.1 Usable Responses and Data Screening

Screening Item	Result	Interpretation
Spreadsheet header rows	1	Excluded from the analytical dataset.
Valid respondent records	123	All records retained for quantitative analysis.
Closed Likert items analyzed	34 items	Q7–Q40, coded from 1 to 5.
Missing values in Likert items	0	No missing values in required Likert items.
Open-ended questions	Used thematically	Voluntary non-responses did not affect hypothesis tests.

Table 4.1 confirms that the dataset was complete for the required Likert-scale items. Nevertheless, the findings remain limited by the self-reported and cross-sectional nature of the data.

4.3 Respondent Profile

The sample included several construction disciplines, although planning-related roles formed the largest group. Planning engineers represented 39.0% of respondents and planning was the most frequently reported main area of work (36.6%). The remaining participants included project management, site and construction engineering, cost control, procurement, consultancy, QA/QC, HSE, and other project-related functions. The sample is therefore multidisciplinary but not evenly distributed across disciplines.

Table 4.2 Respondent Profile Summary

Question	Largest Category	Frequency	Percent
What is your current job position?	Planning Engineer	48	39.0%
What is your main area of work?	Planning	45	36.6%
How many years of experience do you have in the construction industry?	More than 10 years	57	46.3%
What type of construction projects do you mainly work on?	Infrastructure	44	35.8%
Have you used or dealt with AI-based tools in construction project management?	Yes	90	73.2%
What is your level of knowledge about Artificial Intelligence in construction projects?	Moderate	60	48.8%

Most respondents had substantial industry experience: 46.3% reported more than 10 years and 35.8% reported 6–10 years. In addition, 73.2% stated that they had used or dealt with AI-based tools in construction project management. Because many respondents had substantial experience and prior exposure to AI-based tools, their responses are practically relevant to construction project-management settings. However, the concentration of planning and project-control professionals means that the results may reflect the perspectives of professionals who are more familiar with scheduling, reporting, monitoring, and data-driven project control.

4.4 Reliability Analysis

Cronbach's Alpha was calculated to assess the internal consistency of each composite construct. The coefficients ranged from .855 to .928, indicating good to excellent reliability across the main study variables. The total-scale coefficient was .960; however, because the questionnaire measures several conceptually distinct constructs, the construct-specific coefficients provide the more meaningful evidence for interpreting the composite scores. These results support the internal consistency of the measures used in this study, although they do not by themselves confirm the

underlying factor structure of the constructs. Therefore, the reliability findings should be interpreted as evidence that the items within each construct are consistently related, not as full validation of the measurement model.

Table 4.3 Reliability Analysis Using Cronbach's Alpha

Construct	Items	Valid N	Cronbach's Alpha	Interpretation
AI Adoption	8	123	0.855	Good
Construction Project Performance	10	123	0.915	Excellent
Decision-Making Efficiency	10	123	0.928	Excellent
AI Implementation Considerations	6	123	0.865	Good
Total Scale	34	123	0.960	Excellent

4.5 Descriptive Statistics of the Study Variables

Construct means were calculated to describe the overall direction of respondents' perceptions. AIA, CPP, and DME means indicate the extent of favorable perceptions toward AI adoption, perceived project performance, and decision-making efficiency. By contrast, the AIC mean should be read as the level of recognition of implementation-related considerations, including barriers, readiness issues, ethical concerns, and the human-AI support item, rather than as a purely negative challenge score.

Table 4.4 Descriptive Statistics of Main Study Variables

Variable	N	Mean	Std. Deviation	Minimum	Maximum	Level
AI Adoption	123	3.778	0.646	1.625	5.000	High
Construction Project Performance	123	3.410	0.722	1.400	5.000	High
Decision-Making Efficiency	123	3.667	0.706	1.100	5.000	High
AI Challenges / Implementation Considerations	123	3.924	0.803	1.000	5.000	High

AIA recorded a mean of 3.778 (SD = 0.646), indicating generally favorable perceptions of AI use in planning, monitoring, reporting, risk identification, and coordination. DME recorded a mean of 3.667 (SD = 0.706), showing agreement that AI can strengthen decision speed, accuracy, evidence use, and comparison of alternatives. CPP had the lowest construct mean, 3.410 (SD = 0.722), suggesting that respondents were more confident about decision-support benefits than about direct project outcomes. AIC recorded a mean of 3.924 (SD = 0.803); this value reflects

recognition of data, skills, management, privacy, change, and human-oversight considerations rather than a single-direction measure of resistance.

4.6 Correlation Analysis

Pearson correlation analysis was used to examine the direction and strength of the relationships among the main study constructs. AIA was strongly and positively correlated with CPP ($r = .713$, $p < .001$) and DME ($r = .772$, $p < .001$), while DME was also positively correlated with CPP ($r = .670$, $p < .001$). The strongest relationship was between AIA and DME, suggesting that respondents who reported stronger AI adoption also tended to report higher perceived decision-making efficiency. These coefficients provide statistical support for the expected associations in the research model, but they do not establish causal direction because the data are cross-sectional and perception based. Positive correlations involving AIC should not be read as evidence that challenges improve outcomes. Rather, higher AIC scores reflect stronger recognition of implementation-related issues, including readiness, barriers, ethical concerns, and the supportive human-AI role item, rather than a purely negative barrier score.

Table 4.5 Pearson Correlation Summary

Variable 1	Variable 2	N	Pearson r	Sig.	Interpretation
AI Adoption	Construction Project Performance	123	0.713	< .001	Strong positive
AI Adoption	Decision-Making Efficiency	123	0.772	< .001	Strong positive
AI Adoption	AI Challenges / Implementation Considerations	123	0.700	< .001	Strong positive
Construction Project Performance	Decision-Making Efficiency	123	0.670	< .001	Moderate-to-strong positive
Construction Project Performance	AI Challenges / Implementation Considerations	123	0.571	< .001	Moderate positive
Decision-Making Efficiency	AI Challenges / Implementation Considerations	123	0.656	< .001	Moderate-to-strong positive

Overall, the correlation results indicate that favorable perceptions of AI adoption are closely linked with favorable perceptions of decision-making efficiency and construction project performance within the surveyed sample.

4.7 Regression Analysis and Hypothesis Testing

Simple linear regressions were used to test H1–H4 at $\alpha = .05$. The coefficients show predictive associations among composite survey scores. A statistically significant result supports the presence of a relationship in this sample, but does not by itself establish causality or confirm that an implementation barrier has a negative effect.

Table 4.6 Regression-Based Hypothesis Testing

Hyp.	Dependent Variable	Predictor	R	R ²	B	t	Sig.	Decision
H1	Construction Project Performance	AI Adoption	0.713	0.508	0.796	11.176	< .001	Supported
H2	Decision-Making Efficiency	AI Adoption	0.772	0.596	0.844	13.374	< .001	Supported
H3	Construction Project Performance	Decision-Making Efficiency	0.670	0.449	0.685	9.929	< .001	Supported
H4	AI Adoption	AI Challenges / Implementation Considerations	0.700	0.490	0.564	10.785	< .001	Partially supported; direction qualified

- H1 was supported: AIA significantly predicted CPP, $B = 0.796$, $t = 11.176$, $p < .001$, with $R^2 = .508$. Thus, AIA accounted for 50.8% of the observed variance in perceived CPP scores within this sample.
- H2 was supported: AIA significantly predicted DME, $B = 0.844$, $t = 13.374$, $p < .001$, with $R^2 = .596$. This was the strongest simple regression and indicates that respondents with higher AI adoption scores also tended to report higher perceived decision-making efficiency
- H3 was supported: DME significantly predicted CPP, $B = 0.685$, $t = 9.929$, $p < .001$, with $R^2 = .449$. The result is consistent with the proposition that timely, accurate, and evidence-based decisions are associated with better perceived project performance.
- H4 received partial and qualified support. AIC significantly predicted AIA, $B = 0.564$, $t = 10.785$, $p < .001$, with $R^2 = .490$. However, the positive direction cannot be interpreted as evidence that barriers improve adoption, because the AIC composite measures recognition of implementation issues and includes the positively worded human-AI support item. The result establishes a significant association, but not the hypothesized negative barrier effect.

Overall, the regression results provide statistical support for the main relationships proposed in the model, but they should be interpreted as associations among self-reported composite scores rather than evidence of verified project-level causal effects.

4.8 Exploratory Indirect-Effect and Combined Regression Analysis

A multiple regression model was estimated with AIA and DME entered simultaneously as predictors of CPP. The model evaluates whether DME explains additional variation in CPP after AIA is included and is also used to support an exploratory indirect-effect calculation. This analysis is supplementary to the main hypothesis tests and is interpreted cautiously because the study is cross-sectional and based on self-reported survey scores.

Table 4.7 Combined Regression and Exploratory Indirect-Effect Summary

Predictor / Test	B / Effect	Std. Error / Adj. R ²	Beta / F / z	t / Sig.	Sig.
Constant	0.257	0.268	—	0.958	0.340
AI Adoption	0.541	0.108	0.484	4.982	< .001
Decision-Making Efficiency	0.303	0.099	0.296	3.052	0.003
Model Summary	R ² = 0.543	Adj. R ² = 0.536	F = 71.404	p < .001	—
Exploratory Sobel Indirect Effect	Effect = 0.256	—	z = 2.975	p = 0.003	—

The combined model was statistically significant, $F = 71.404$, $p < .001$, and accounted for 54.3% of the variance in perceived CPP scores, with an adjusted R^2 of .536. Both AIA ($B = 0.541$, $p < .001$) and DME ($B = 0.303$, $p = .003$) remained significant predictors in the combined model. Compared with the AIA-only model ($R^2 = .508$), adding DME increased explained variance by 3.5 percentage points, indicating that DME added a modest amount of explanatory value beyond AIA, although the two predictors shared substantial variance. The Sobel test produced an estimated indirect effect of 0.256, $z = 2.975$, $p = .003$. This result is consistent with a possible partial indirect pathway from AIA to perceived CPP through DME, but it is reported as exploratory because the design is cross-sectional and no bootstrapped confidence interval was available. In practical terms, the finding suggests that AI adoption may be linked to perceived project performance partly through its relationship with faster, more accurate, and more evidence-based decision-making, although this pathway should be confirmed in future longitudinal or bootstrapped studies.

4.9 AI as a Supportive Tool Rather Than a Replacement

The human-AI role item was tested separately against the neutral midpoint of 3 because it reflects a positive support-oriented view of AI rather than a barrier item. The mean score was 4.195 (SD = 1.084), and the one-sample t-test was statistically significant, $t(122) = 12.229$, $p < .001$. This result indicates that respondents generally agreed that AI should support engineers and project managers rather than replace them. The finding is important because many respondents were experienced construction professionals and 73.2% used or dealt with AI-based tools in construction project management. However, the result reflects professional perceptions within this sample and should not be interpreted as direct evidence about actual workforce replacement outcomes.

Table 4.8 One-Sample Test for AI Supportive Role

Item	N	Mean	Std. Deviation	Test Value	t	Sig.	Decision
AI should support engineers and project managers rather than replace them	123	4.195	1.084	3.000	12.229	< .001	Supported

Overall, the result supports the human-AI collaboration position adopted in this thesis: AI is viewed as a decision-support tool that should strengthen, not replace, professional judgment in construction project management.

4.10 Open-Ended Response Summary

The open-ended responses were used to add context to the quantitative findings by showing how respondents described AI benefits, implementation challenges, and the human-AI relationship in their own words. Responses were coded into recurring themes using a descriptive thematic approach. A single response could receive more than one thematic code; consequently, the theme counts do not sum to the number of respondents. The most frequent benefit themes concerned scheduling and delay prediction, data analysis and reporting, productivity, cost control, and risk or safety. The most frequent challenge themes concerned data quality and privacy, limited knowledge and training, resistance to change, implementation cost, and management support.

Table 4.9 Open-Ended Response Themes

Question	Responses Used	Main Themes
Main benefits of AI	101	Time, scheduling, and delay prediction (45); Data analysis, reporting, and decision support (45); Productivity and resource efficiency (21); Cost control and estimation (20); Risk and safety management (14)
Main challenges of AI	98	Data quality, privacy, and security concerns (33); Lack of knowledge, skills, and training (29); Resistance to change and adoption culture (29); Implementation cost and investment requirements (25); Lack of management support and governance (12)
AI replacement view	103	AI supports but does not fully replace engineers/managers (80); Unclear / mixed answer (23)

The benefit themes indicate that respondents mainly connected AI with practical project-control functions, especially scheduling, delay prediction, reporting, productivity, cost control, and risk/safety monitoring. The challenge themes suggest that respondents did not view AI adoption as a purely technical issue; instead, they linked successful implementation to data quality, privacy, training, organizational culture, cost, and management support. This pattern is consistent with the interpretation of AIC as a set of AI-related implementation considerations rather than only negative barriers. The responses on AI replacement also reinforce the result reported in Section 4.9, as most coded responses favored AI as a supportive tool rather than a full substitute for engineers or project managers.

4.11 Item-Level Descriptive Statistics

Item-level means were examined to identify patterns that may not be visible from the composite construct averages alone. This analysis helps show whether respondents viewed AI more favorably in some project-management functions than in others. The item statements are reported in summarized form and should be interpreted as professional perceptions of AI's potential contribution, not as verified project-level outcomes.

Table 4.10 Item-Level Descriptive Statistics for Likert-Scale Questions

Item Code	Statement Summary	Mean	Std. Dev.	Level
AIA1	AI tools can support construction project planning, execution, and monitoring.	4.130	0.849	High
AIA2	AI can help in predicting project delays before they occur.	3.545	0.952	High

Item Code	Statement Summary	Mean	Std. Dev.	Level
AIA3	AI can improve cost estimation and budget control in construction projects.	3.789	0.871	High
AIA4	AI can help identify potential risks in construction projects.	3.650	0.868	High
AIA5	AI can improve site progress monitoring and daily reporting.	3.829	0.964	High
AIA6	AI tools can improve the accuracy of project reports and performance data.	4.016	0.905	High
AIA7	AI can help reduce human errors in construction project management.	3.618	0.937	High
AIA8	The use of AI can improve coordination between planning, site, procurement, and management teams.	3.650	0.983	High
CPP1	AI can improve the overall performance of construction projects.	3.455	0.899	High
CPP2	AI can help reduce project delays.	3.358	0.942	Moderate
CPP3	AI can help reduce project cost overruns.	3.268	1.033	Moderate
CPP4	AI can improve the quality of construction project outputs.	3.374	0.944	Moderate
CPP5	AI can support better allocation of manpower, materials, and equipment.	3.472	0.952	High
CPP6	AI can improve productivity in construction site activities.	3.154	1.064	Moderate
CPP7	AI can contribute to better safety performance on construction sites.	3.065	1.006	Moderate
CPP8	AI can help track material availability and delivery status.	3.780	0.954	High

Item Code	Statement Summary	Mean	Std. Dev.	Level
CPP9	AI can improve subcontractor performance monitoring.	3.545	0.917	High
CPP10	AI can support better control of project time, cost, quality, and safety.	3.626	0.872	High
DME1	AI can help project managers and engineers make faster decisions.	3.740	0.948	High
DME2	AI can improve the accuracy of decision-making in construction projects.	3.748	0.865	High
DME3	AI can provide useful data analysis for project decision-making.	3.959	0.872	High
DME4	AI can help compare different project alternatives before making decisions.	3.967	0.877	High
DME5	AI can support decision-making during project risks and uncertainties.	3.650	0.923	High
DME6	AI can improve the ability to solve site and construction problems quickly.	3.455	0.952	High
DME7	AI can help management make evidence-based decisions.	3.561	0.916	High
DME8	AI can reduce dependence on personal judgment only when making project decisions.	3.293	1.046	Moderate
DME9	AI can improve decisions related to time, cost, resources, procurement, and site execution.	3.667	0.836	High
DME10	AI can support strategic decision-making in construction project management.	3.626	0.824	High

Item Code	Statement Summary	Mean	Std. Dev.	Level
AIC1	Lack of AI knowledge is a major challenge in construction projects.	3.659	1.070	High
AIC2	Resistance to change among employees can limit AI adoption.	3.699	0.975	High
AIC3	Poor data quality can reduce the effectiveness of AI in construction projects.	4.122	0.955	High
AIC4	Lack of management support can limit the use of AI in construction projects.	3.789	1.034	High
AIC5	Ethical concerns, such as data privacy, should be considered when using AI.	4.081	1.106	High
AIC6	AI should support engineers and project managers rather than replace them.	4.195	1.084	High

The highest AIA means were recorded for general planning, execution, and monitoring support ($M = 4.130$) and report/data accuracy ($M = 4.016$). Within DME, analysis of alternatives ($M = 3.967$) and data analysis for decisions ($M = 3.959$) were the strongest items. By contrast, several CPP items were only moderate, including safety performance ($M = 3.065$), site productivity ($M = 3.154$), cost-overrun reduction ($M = 3.268$), delay reduction ($M = 3.358$), and quality improvement ($M = 3.374$). This pattern suggests that respondents perceived AI's value more clearly in information processing, reporting accuracy, alternative comparison, and decision support than in direct improvements to physical project outcomes. This distinction is important because the study measures perceived contribution, not audited project performance. The lower CPP item means indicate that respondents may be more cautious about AI's ability to produce immediate improvements on site unless it is supported by reliable data, trained users, and effective management action. AIC6 should also be interpreted separately from the barrier-oriented AIC items because it reflects support for human-AI collaboration rather than an implementation barrier.

4.12 Graphical Presentation of Survey Results

Figures 4.1–4.7 provide visual summaries of the respondent profile, AI exposure, construct means, reliability, correlations, regression R^2 values, and open-ended themes. They complement rather than replace the numerical tables and hypothesis tests.

Respondents by Main Area of Work

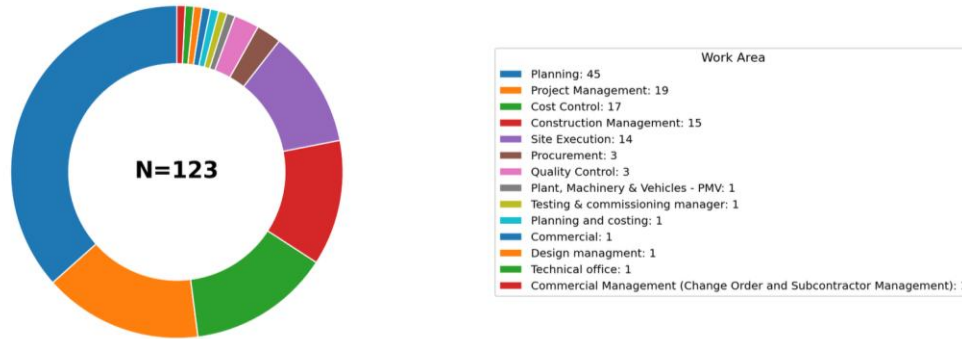


Figure 4.1 Respondents by Main Area of Work

Figure 4.1 confirms the concentration of respondents in planning-related roles while also showing participation from several project functions. This composition supports multidisciplinary interpretation but indicates that planning and project-control perspectives are comparatively influential.

Exposure to AI-Based Tools

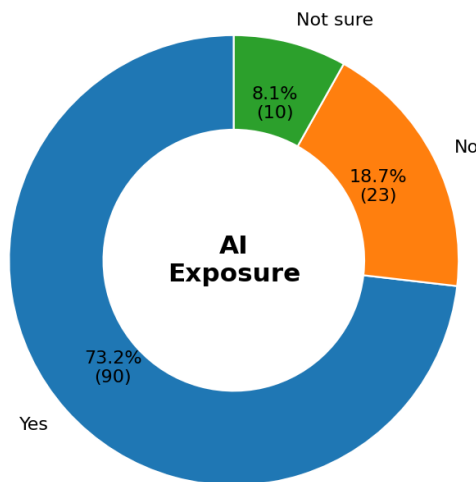


Figure 4.2 Exposure to AI-Based Tools

Figure 4.2 shows that 73.2% of respondents reported exposure to AI-based tools. The finding supports the relevance of the sample while not implying that all respondents had the same depth or type of practical AI experience.

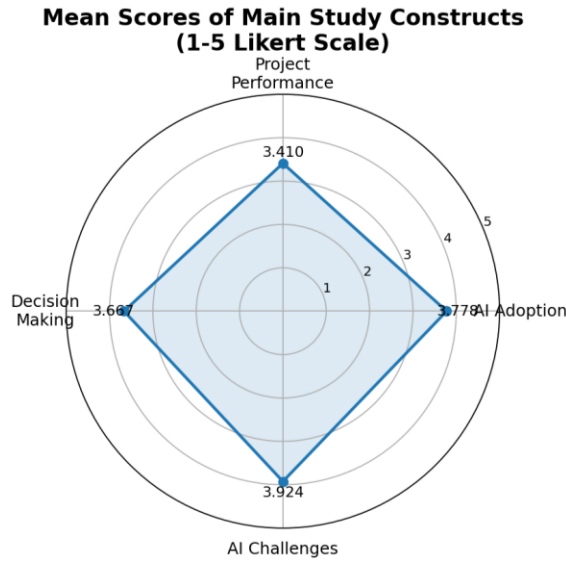


Figure 4.3 Mean Scores of Main Study Constructs

Figure 4.3 shows that all construct means were in the high category. The AIC mean should be read as recognition of implementation considerations, whereas the remaining means represent favorable perceptions of adoption, performance, and decision efficiency.

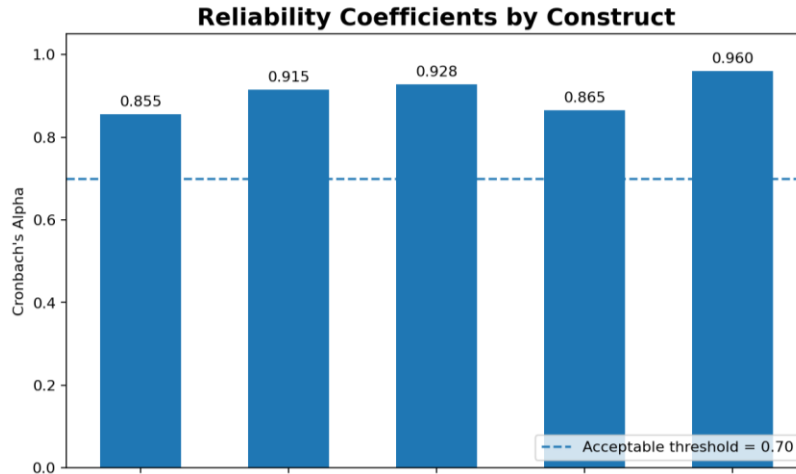


Figure 4.4 Reliability Coefficients by Construct

Figure 4.4 shows that all construct-specific Cronbach's Alpha coefficients exceeded .85, supporting the internal consistency of the composite measures used in subsequent analyses.

Pearson Correlation Matrix among Study Variables

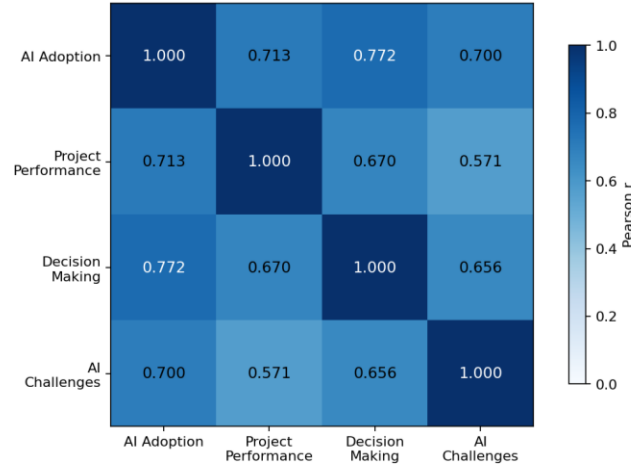


Figure 4.5 Pearson Correlation Coefficients among Study Variables

Figure 4.5 illustrates the positive bivariate relationships among the constructs. The largest coefficient was between AIA and DME ($r = .772$), followed by AIA and CPP ($r = .713$).

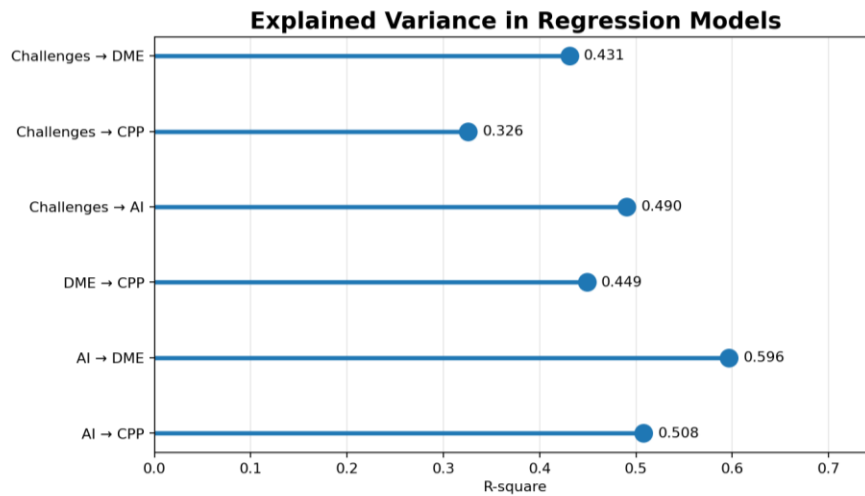


Figure 4.6 Explained Variance in Regression Models

Figure 4.6 compares model R^2 values. AIA accounted for 50.8% of CPP variance and 59.6% of DME variance, while DME accounted for 44.9% of CPP variance. These values describe variation in perception-based survey scores and should not be interpreted as verified causal project gains.

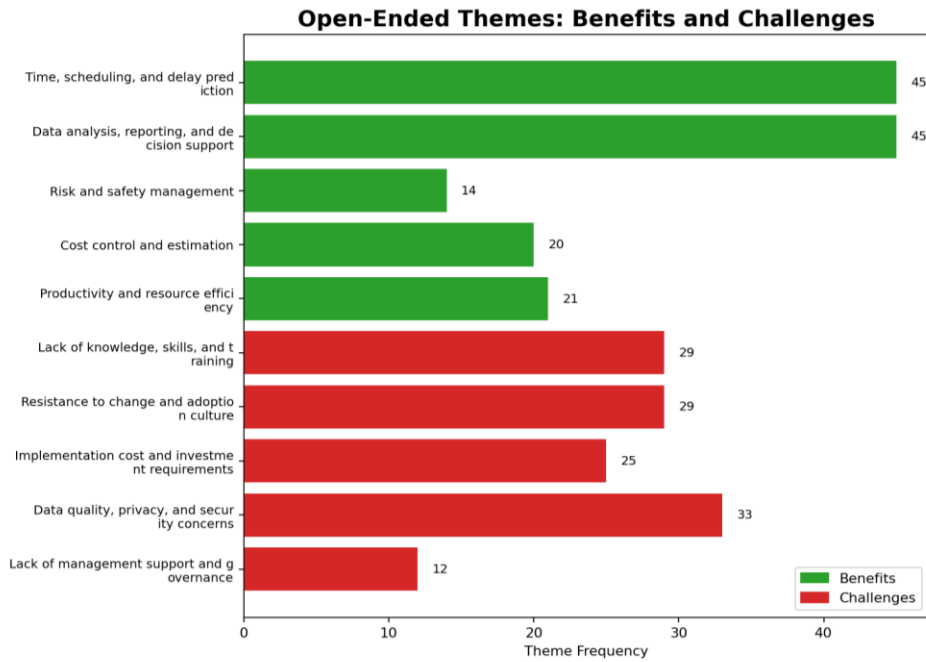


Figure 4.7 Open-Ended Themes: Benefits and Challenges

Figure 4.7 summarizes the coded open-ended themes. The results emphasize that practical AI value and implementation risk coexist: respondents identified potential gains in time, analysis, reporting, productivity, cost, and safety, alongside concerns about data, skills, change, cost, and leadership.

4.13 Item Response Distribution

Response distributions were aggregated by construct to show how strongly answers were concentrated in agreement, neutrality, or disagreement. The distributions provide context that cannot be seen from means alone and show that responses varied across constructs.

Table 4.11 Summary of Response Distribution by Construct

Construct	Item-responses	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Mean
AI Adoption	984	18 (1.8%)	77 (7.8%)	223 (22.7%)	453 (46.0%)	213 (21.6%)	3.778
Construction Project Performance	1,230	60 (4.9%)	132 (10.7%)	409 (33.3%)	502 (40.8%)	127 (10.3%)	3.410
Decision-Making Efficiency	1,230	34 (2.8%)	90 (7.3%)	326 (26.5%)	582 (47.3%)	198 (16.1%)	3.667
AI Challenges / Implementation Considerations	738	23 (3.1%)	51 (6.9%)	151 (20.5%)	247 (33.5%)	266 (36.0%)	3.924

Agreement responses exceeded disagreement responses for every construct. Combined agreement was highest for AIC (69.5%), followed by AIA (67.6%), DME (63.4%), and CPP (51.1%). CPP also contained the largest neutral share (33.3%), which is consistent with its lower mean and the more cautious item-level ratings for direct performance benefits. This suggests that respondents were more confident about AI's role in adoption, information processing, and decision support than about its immediate contribution to physical project outcomes. The high agreement for AIC should not be interpreted as generally negative attitudes toward AI. Instead, it indicates that respondents recognized implementation conditions such as data quality, privacy, training, management support, and the need for human-AI collaboration. Overall, the distribution results reinforce the earlier descriptive findings: respondents were generally positive toward AI adoption and decision support, but more cautious about direct project-performance outcomes.

4.14 Chapter Summary

Chapter Four presented the empirical results from 123 valid responses. The analysis showed good-to-excellent internal consistency for the main constructs and statistically significant positive relationships among AIA, DME, and CPP within the survey data. H1–H3 were supported, indicating that higher AI adoption scores were associated with higher perceived construction project performance and decision-making efficiency, and that higher decision-making efficiency scores were associated with higher perceived project performance. H4 showed a statistically significant association, but it was only partially and conditionally supported because the positive direction did not confirm a negative barrier effect and because AIC includes both barrier-oriented items and the supportive human-AI role item. The combined regression model and Sobel test provided exploratory evidence consistent with a possible indirect pathway through DME, while the one-sample test indicated strong respondent agreement that AI should support engineers and project managers rather than replace them. Overall, the results suggest that AI adoption is linked to perceived project performance partly through decision-making efficiency, but all findings remain limited by the cross-sectional, self-reported nature of the data. Chapter Five discusses these findings in relation to research questions, literature, practical implications, limitations, and recommendations.

CHAPTER FIVE: DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

5.1 Introduction

This chapter discusses the empirical findings from 123 valid responses in relation to the research objectives, hypotheses, and reviewed literature. The discussion focuses on the statistically supported relationships among AI adoption, decision-making efficiency, and perceived construction project performance, while also explaining the qualified interpretation of AI-related implementation considerations and the exploratory indirect-effect result through decision-making efficiency. Because the study is cross-sectional and based on self-reported professional perceptions, the findings are interpreted as associations within the survey data rather than as confirmed causal effects. The chapter also presents the study conclusions, practical recommendations, limitations, suggestions for future research, and an implementation framework for responsible AI adoption in Saudi construction projects.

5.2 Discussion of Findings

5.2.1 AI Adoption and Construction Project Performance

AIA was strongly associated with CPP ($r = .713$), and the simple regression accounted for 50.8% of the variance in perceived performance scores within the survey data. This finding is consistent with literature linking AI to forecasting, monitoring, coordination, document analysis, risk detection, and project-control support (Abioye et al., 2021; Pan & Zhang, 2021; Adebayo et al., 2025). However, the item-level results provide an important qualification: respondents rated AI's contribution to reporting, monitoring, and information accuracy more strongly than its perceived contribution to safety, productivity, cost-overrun reduction, delay reduction, and quality. This pattern may also reflect the composition of the sample, in which planning and project-control professionals formed a large share of respondents and may be more familiar with reporting, monitoring, and data-based decision support. AI should therefore be understood as an enabling capability whose performance value depends on data quality, workflow integration, management action, and professional validation.

5.2.2 AI Adoption and Decision-Making Efficiency

The strongest relationship in the study was between AIA and DME ($r = .772$; $R^2 = .596$). Within this sample, respondents were especially positive about AI's ability to analyze project data and compare alternatives. This supports research arguing that AI creates managerial value by

improving information processing, forecasting, and the evidence available to decision-makers (Holzmann et al., 2022; Taboada et al., 2023; Song et al., 2025). In practical terms, AI may first support the way issues are recognized, analyzed, prioritized, escalated, and followed up before any measurable change appears in final time, cost, quality, or safety indicators.

5.2.3 Decision-Making Efficiency and Project Performance

DME was positively associated with CPP ($r = .670$; $R^2 = .449$), and it remained statistically significant when AIA was entered in the same regression model. The combined model explained 54.3% of the variance in perceived CPP scores, only 3.5 percentage points more than AIA alone, indicating that AIA and DME shared substantial explanatory information. The significant Sobel result is consistent with a possible partial indirect pathway, but the evidence remains exploratory rather than causal because temporal order was not established and bootstrapped mediation was not performed. The appropriate conclusion is that decision-making efficiency is a plausible performance mechanism that should be examined more rigorously in future longitudinal or structural-equation studies.

5.2.4 AI Challenges and Implementation Considerations

The high AIC mean suggests that respondents recognized the importance of skills, change management, data quality, leadership support, privacy, and human oversight. This is consistent with adoption literature identifying organizational readiness and trust as conditions for effective AI use (Regona et al., 2022; Salimimoghadam et al., 2025). H4, however, requires cautious interpretation. The positive association between AIC and AIA does not show that challenges improve adoption; it may indicate that respondents who are more aware of AI also recognize its implementation requirements. In addition, the AIC composite includes a positive human-AI role item. The result therefore supports the relevance of AI-related implementation considerations, not a simple negative barrier effect.

5.2.5 AI as a Supportive Tool Rather Than a Replacement

Respondents showed strong agreement that AI should support rather than replace engineers and project managers ($M = 4.195$; $t(122) = 12.229$; $p < .001$). The open-ended responses produced the same general pattern, with most coded responses favoring a supportive rather than substitutive role for AI. This aligns with AEC research emphasizing explainability, reliability, privacy, accountability, and professional oversight (Emaminejad & Akhavian, 2022; Liang et al., 2023).

The implication is not that professional roles will remain unchanged, but that responsible adoption should assign AI to data-intensive and repetitive analytical tasks while retaining human responsibility for safety, contractual interpretation, ethics, stakeholder negotiation, and final approval.

5.3 Conclusions

The findings indicate that AI adoption is most strongly linked to decision-making efficiency and is also positively associated with perceived construction project performance. Within the survey data, AI appears to provide the greatest value when it supports information processing, reporting, monitoring, alternative comparison, and evidence-based decision-making. The results also show that AI's value is not automatic; it depends on data quality, workflow integration, management action, user capability, and professional validation.

H1 was supported: higher AIA scores were associated with higher perceived CPP scores ($r = .713$; $R^2 = .508$).

H2 was supported and produced the strongest relationship: AIA was closely associated with DME ($r = .772$; $R^2 = .596$).

H3 was supported: DME was positively associated with CPP ($r = .670$; $R^2 = .449$) and remained significant in the combined model.

The exploratory indirect-effect analysis was statistically significant, but the cross-sectional design does not establish causal mediation.

H4 was only partially supported: AIC was significantly associated with AIA, but the positive direction and mixed item content mean that the result should be interpreted as evidence of implementation awareness rather than as a negative barrier effect.

Table 5.1 Summary of Findings and Recommendations

Finding	Interpretation	Recommendation
AI adoption is statistically associated with perceived project performance	AI appears most relevant to perceived project performance when applied to project-control, reporting, monitoring, and site-management processes.	Apply AI to practical use cases such as reporting, progress monitoring, cost forecasting, and delay prediction.

Finding	Interpretation	Recommendation
AI adoption is strongly associated with decision-making efficiency	Respondents perceived AI as useful for faster and more evidence-based decision-making.	Train teams to interpret AI outputs and convert them into accountable project actions.
Decision-making efficiency is associated with perceived project performance	Efficient decisions are linked to stronger perceived project results.	Improve workflows, approval cycles, information quality, and decision accountability.
Implementation considerations are significantly associated with adoption	The relationship shows awareness of implementation requirements; it does not demonstrate that barriers improve adoption.	Separate barriers, readiness, ethics, and human-AI role measures in future evaluations.
AI is perceived as a supportive tool rather than a replacement	Professional judgment remains necessary for safety, contractual interpretation, ethics, stakeholder coordination, and final approval.	Use AI as decision support while maintaining human responsibility.

5.4 Practical Recommendations

Based on the findings, construction organizations should adopt AI gradually and focus on controlled, measurable, and human-supervised implementation rather than rapid organization-wide deployment.

- Begin with one or two high-value, low-risk use cases, such as progress-report summarization, procurement-risk alerts, document search, or forecast support, rather than launching organization-wide AI at once.
- Establish a data-readiness baseline covering completeness, revision control, ownership, naming conventions, access rights, and update frequency before training or deploying an AI solution.
- Define project-specific pilot KPIs such as reporting cycle time, forecast accuracy, decision turnaround time, rework frequency, late-material alerts, or safety-observation closure time.
- Train users to interpret uncertainty, verify outputs, identify hallucinated or biased information, protect confidential data, and document the basis of AI-supported decisions.
- Maintain human approval for safety-critical, quality-critical, contractual, commercial, personnel, and regulatory decisions, with responsibility assigned through the existing authority matrix and approved project procedures.
- Create an AI governance procedure covering permitted tools and data, privacy, cybersecurity, validation, audit trails, vendor review, model monitoring, incident reporting, and periodic benefit reassessment.
-

5.5 Recommendations for Academic and Professional Practice

Universities, professional bodies, and training providers should integrate applied AI into construction and project-management education. Programs should combine tool use with data literacy, statistical interpretation, project controls, ethics, privacy, cybersecurity awareness, and the evaluation of AI outputs.

Professional guidance should also clarify accountability. An AI recommendation should be documented, reviewed by a competent person, and approved through the project's existing authority matrix before it influences safety-critical, contractual, commercial, quality, or regulatory decisions.

5.6 Study Limitations

The study findings should be interpreted considering several methodological limitations:

- The cross-sectional design does not establish temporal order or causality.
- Purposive, referral-supported sampling and the concentration of planning-related respondents limit representativeness and generalizability.
- The distribution denominator was unknown, so a conventional survey response rate could not be calculated.
- All main constructs were collected from the same self-report instrument, creating possible common-method, social-desirability, and knowledge-level bias.
- Perceived performance was not validated against objective schedule, cost, quality, safety, or productivity records.
- Construct validity was not tested through exploratory or confirmatory factor analysis.
- The AIC composite contains a conceptually distinct human-AI role item, which requires cautious interpretation.

5.7 Suggestions for Future Research

Future research can strengthen and extend the present findings in several ways:

- Use stratified or probability-based sampling across owners, consultants, contractors, regions, project types, and professional disciplines.

- Where feasible, link survey measures to objective project indicators such as schedule variance, cost variance, rework, safety observations, procurement delay, decision-cycle time, and productivity.
- Apply longitudinal or quasi-experimental designs to examine changes in performance before and after a defined AI implementation.
- Refine the measurement model by separating implementation barriers, organizational readiness, ethics/governance, and human-AI role perceptions, then test construct validity through exploratory and confirmatory factor analysis.
- Test the indirect role of DME using bootstrapped mediation or structural equation modeling with adequate sample size, model diagnostics, and confidence intervals.

5.8 Practical Implementation Framework

The implementation framework translates the findings into a staged management process. It begins with data readiness, proceeds through controlled pilots and user capability building, establishes governance and human review, measures project-relevant KPIs, and scales only those applications that demonstrate reliable value.

5.8.1 Practical Interpretation of the Findings for Saudi Construction Projects

The results indicate that AI adoption should be managed as a decision-improvement program, not merely as a software purchase. Within the survey data, the strongest relationship was between AI adoption and decision-making efficiency, suggesting that early benefits are likely to appear in information retrieval, forecasting, comparison of alternatives, reporting cycle time, and risk escalation. Organizations should connect these capabilities to existing approval workflows, responsibility matrices, and project-control routines so that analytical outputs lead to accountable action.

Use cases should reflect stakeholder responsibilities. Contractors may prioritize progress visibility, productivity, procurement risk, cost trends, and subcontractor follow-up. Consultants may prioritize document review, design coordination, inspection planning, and quality trends. Owners and project-management offices may prioritize portfolio dashboards, governance, cross-project risk, and performance assurance. In every case, the baseline process and expected benefit should be defined before implementation.

The high recognition of implementation considerations indicates that AI scale-up should be evidence-based rather than enthusiasm-driven. Each pilot should specify the data owner, input standard, validation method, accountable reviewer, decision boundary, privacy controls, expected KPI, and fallback procedure. Applications that cannot demonstrate reliable data, interpretable outputs, and measurable workflow improvement should not be expanded. This staged approach helps organizations adopt AI responsibly while maintaining professional accountability and project-level control.

5.8.2 Implementation Roadmap

Table 5.2 AI Implementation Roadmap for Saudi Construction Organizations

Stage	Main Action	Expected Output	Success Indicator
1. Data readiness	Standardize project data, document coding, reporting frequency, and responsibility matrix	Reliable project data environment	Reduced missing or inconsistent project data
2. Pilot AI tools	Apply AI on a limited use case such as progress reporting, procurement risk, or cost forecasting	Controlled proof of value	Clear improvement compared with current process
3. Train users	Train engineers, planners, cost teams, and managers on AI interpretation and limitations	Improved user acceptance	Increased adoption and fewer interpretation errors
4. Governance and ethics	Define privacy rules, approval rights, accountability, and human review requirements	Responsible AI use	No unmanaged confidential or biased outputs
5. Measure KPIs	Track time saved, decision cycle time, forecast accuracy, rework reduction, or safety observations	Evidence of performance contribution	Measurable KPI improvement
6. Scale adoption	Expand successful use cases across projects and departments	Organizational AI capability	Repeatable AI-supported workflows

AI Implementation Roadmap for Saudi Construction Projects

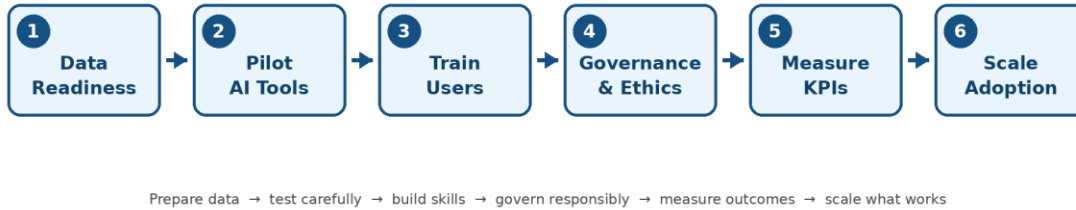


Figure 5.1 Recommended AI Implementation Roadmap for Saudi Construction Projects

Table 5.2 and Figure 5.1 present a six-stage roadmap. Data readiness comes first because incomplete or inconsistent records can produce misleading outputs. Controlled pilots reduce technical and organizational risk. Training, governance, KPI measurement, and gradual scale-up ensure that adoption remains accountable and tied to project value.

5.8.3 Recommendations by Stakeholder Group

Table 5.3 Recommendations by Stakeholder Group

Stakeholder	Recommended Actions	Expected Benefit
Contractors	Use AI for progress monitoring, look-ahead risks, productivity analysis, cost trend detection, and subcontractor follow-up	Improved control of time, cost, quality, safety, and resources
Consultants	Apply AI to document review, inspection planning, quality trends, technical correspondence, and design coordination	Faster review cycles and stronger technical decision support
Project owners	Develop AI governance requirements, data standards, dashboard expectations, and ethical guidelines in project controls	Better transparency and comparable performance information across projects
Project managers	Use AI outputs as decision-support evidence while retaining professional accountability and stakeholder coordination	Faster and more evidence-based decision-making
Planning and cost teams	Integrate AI predictions with Primavera P6, cost reports, procurement logs, and earned-value indicators	Earlier identification of schedule and cost deviations
Universities and training providers	Add applied AI, data analytics, digital project controls, and AI ethics to construction and project-management programs	Improved future workforce readiness

Stakeholder	Recommended Actions	Expected Benefit
Policy and industry bodies	Promote responsible AI guidance, data privacy awareness, and digital transformation standards for construction projects	Safer and more consistent AI adoption across the industry

The stakeholder recommendations show that AI implementation is an organization-wide responsibility. Project controls, engineering, construction, procurement, commercial, QA/QC, HSE, IT, data-governance, and senior-management functions should jointly define use cases and controls. Assigning AI solely to an IT team would separate the technology from the construction decisions it is intended to support.

5.8.4 Contribution to Knowledge and Practice

The study contributes empirical evidence from a Saudi construction context by examining AIA, DME, CPP, and AI-related implementation considerations within one survey model. Within the survey data, its principal contribution is the finding that AI's strongest perceived value lies in decision-making efficiency, while direct project-performance benefits receive more cautious ratings. This distinction helps explain how AI may support construction project management without assuming that technology automatically improves project outcomes.

The study also contributes a human-centered adoption perspective. Respondents viewed AI primarily as decision support, and the findings identify data quality, skills, leadership, privacy, governance, and human oversight as necessary implementation conditions. The resulting framework therefore combines technology adoption with professional accountability and measurable project-management outcomes. Because the evidence is based on self-reported perceptions, the contribution should be understood as empirical perception-based evidence rather than direct proof of audited project-performance improvement.

5.9 Final Conclusion

This study found strong positive associations between AI adoption, decision-making efficiency, and perceived construction project performance among 123 construction professionals in Saudi Arabia. Within this sample, the evidence suggests that AI is perceived to support project work by improving data analysis, forecasting, reporting, monitoring, and the comparison of alternatives. However, the results do not establish that AI alone causes better project outcomes, and the exploratory indirect-effect analysis should be interpreted only as evidence consistent with a possible indirect pathway rather than definitive mediation. Effective implementation requires

reliable data, trained users, management support, clear governance, and human accountability. The central conclusion is that AI should be adopted as a controlled decision-support capability that enhances, but does not replace, the professional judgment and responsibility of engineers and project managers.

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APPENDIX A: FINAL QUESTIONNAIRE

Title: The Impact of Artificial Intelligence on Construction Project Performance and Decision-Making Efficiency

Introduction: Dear Participant, this questionnaire is part of an academic research study that aims to examine the impact of Artificial Intelligence (AI) on construction project performance and decision-making efficiency. Your responses will be used for academic purposes only.

Participation is voluntary, and all information will remain confidential and anonymous. Please answer the following questions based on your experience in construction projects.

Response Scale for Sections B to E: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Appendix A.1 Final Questionnaire Items

No.	Question / Item
1	What is your current job position?
2	What is your main area of work?
3	How many years of experience do you have in the construction industry?
4	What type of construction projects do you mainly work on?
5	Have you used or dealt with AI-based tools in construction project management?
6	What is your level of knowledge about Artificial Intelligence in construction projects?
7	Artificial Intelligence Adoption [7. AI tools can support construction project planning, execution, and monitoring.]
8	Artificial Intelligence Adoption [8. AI can help in predicting project delays before they occur.]
9	Artificial Intelligence Adoption [9. AI can improve cost estimation and budget control in construction projects.]
10	Artificial Intelligence Adoption [10. AI can help identify potential risks in construction projects.]
11	Artificial Intelligence Adoption [11. AI can improve site progress monitoring and daily reporting.]
12	Artificial Intelligence Adoption [12. AI tools can improve the accuracy of project reports and performance data.]
13	Artificial Intelligence Adoption [13. AI can help reduce human errors in construction project management.]
14	Artificial Intelligence Adoption [14. The use of AI can improve coordination between planning, site, procurement, and management teams.]
15	Construction Project Performance [15. AI can improve the overall performance of construction projects.]
16	Construction Project Performance [16. AI can help reduce project delays.]
17	Construction Project Performance [17. AI can help reduce project cost overruns.]
18	Construction Project Performance [18. AI can improve the quality of construction project outputs.]
19	Construction Project Performance [19. AI can support better allocation of manpower, materials, and equipment.]
20	Construction Project Performance [20. AI can improve productivity in construction site activities.]

No.	Question / Item
21	Construction Project Performance [21. AI can contribute to better safety performance on construction sites.]
22	Construction Project Performance [22. AI can help track material availability and delivery status.]
23	Construction Project Performance [23. AI can improve subcontractor performance monitoring.]
24	Construction Project Performance [24. AI can support better control of project time, cost, quality, and safety.]
25	Decision-Making Efficiency [25. AI can help project managers and engineers make faster decisions.]
26	Decision-Making Efficiency [26. AI can improve the accuracy of decision-making in construction projects.]
27	Decision-Making Efficiency [27. AI can provide useful data analysis for project decision-making.]
28	Decision-Making Efficiency [28. AI can help compare different project alternatives before making decisions.]
29	Decision-Making Efficiency [29. AI can support decision-making during project risks and uncertainties.]
30	Decision-Making Efficiency [30. AI can improve the ability to solve site and construction problems quickly.]
31	Decision-Making Efficiency [31. AI can help management make evidence-based decisions.]
32	Decision-Making Efficiency [32. AI can reduce dependence on personal judgment only when making project decisions.]
33	Decision-Making Efficiency [33. AI can improve decisions related to time, cost, resources, procurement, and site execution.]
34	Decision-Making Efficiency [34. AI can support strategic decision-making in construction project management.]
35	Challenges of Using AI [35. Lack of AI knowledge is a major challenge in construction projects.]
36	Challenges of Using AI [36. Resistance to change among employees can limit AI adoption.]
37	Challenges of Using AI [37. Poor data quality can reduce the effectiveness of AI in construction projects.]
38	Challenges of Using AI [38. Lack of management support can limit the use of AI in construction projects.]
39	Challenges of Using AI [39. Ethical concerns, such as data privacy, should be considered when using AI.]
40	Challenges of Using AI [40. AI should support engineers and project managers rather than replace them.]
41	In your opinion, what are the main benefits of using AI in construction project management?
42	What are the main challenges that may prevent the use of AI in construction projects?
43	Do you think AI can replace engineers or project managers in construction projects? Why?

APPENDIX B: ITEM-TO-VARIABLE MAPPING

Table B.1 Item-to-Variable Mapping

Item Code	Variable	Questionnaire Item
AIA1	Artificial Intelligence Adoption	7. AI tools can support construction project planning, execution, and monitoring.
AIA2	Artificial Intelligence Adoption	8. AI can help in predicting project delays before they occur.
AIA3	Artificial Intelligence Adoption	9. AI can improve cost estimation and budget control in construction projects.
AIA4	Artificial Intelligence Adoption	10. AI can help identify potential risks in construction projects.
AIA5	Artificial Intelligence Adoption	11. AI can improve site progress monitoring and daily reporting.
AIA6	Artificial Intelligence Adoption	12. AI tools can improve the accuracy of project reports and performance data.
AIA7	Artificial Intelligence Adoption	13. AI can help reduce human errors in construction project management.
AIA8	Artificial Intelligence Adoption	14. The use of AI can improve coordination between planning, site, procurement, and management teams.
CPP1	Construction Project Performance	15. AI can improve the overall performance of construction projects.
CPP2	Construction Project Performance	16. AI can help reduce project delays.
CPP3	Construction Project Performance	17. AI can help reduce project cost overruns.
CPP4	Construction Project Performance	18. AI can improve the quality of construction project outputs.
CPP5	Construction Project Performance	19. AI can support better allocation of manpower, materials, and equipment.
CPP6	Construction Project Performance	20. AI can improve productivity in construction site activities.
CPP7	Construction Project Performance	21. AI can contribute to better safety performance on construction sites.
CPP8	Construction Project Performance	22. AI can help track material availability and delivery status.
CPP9	Construction Project Performance	23. AI can improve subcontractor performance monitoring.
CPP10	Construction Project Performance	24. AI can support better control of project time, cost, quality, and safety.
DME1	Decision-Making Efficiency	25. AI can help project managers and engineers make faster decisions.
DME2	Decision-Making Efficiency	26. AI can improve the accuracy of decision-making in construction projects.
DME3	Decision-Making Efficiency	27. AI can provide useful data analysis for project decision-making.
DME4	Decision-Making Efficiency	28. AI can help compare different project alternatives before making decisions.
DME5	Decision-Making Efficiency	29. AI can support decision-making during project risks and uncertainties.
DME6	Decision-Making Efficiency	30. AI can improve the ability to solve site and construction problems quickly.
DME7	Decision-Making Efficiency	31. AI can help management make evidence-based decisions.

Item Code	Variable	Questionnaire Item
DME8	Decision-Making Efficiency	32. AI can reduce dependence on personal judgment only when making project decisions.
DME9	Decision-Making Efficiency	33. AI can improve decisions related to time, cost, resources, procurement, and site execution.
DME10	Decision-Making Efficiency	34. AI can support strategic decision-making in construction project management.
AIC1	AI Challenges / Human-AI Relationship	35. Lack of AI knowledge is a major challenge in construction projects.
AIC2	AI Challenges / Human-AI Relationship	36. Resistance to change among employees can limit AI adoption.
AIC3	AI Challenges / Human-AI Relationship	37. Poor data quality can reduce the effectiveness of AI in construction projects.
AIC4	AI Challenges / Human-AI Relationship	38. Lack of management support can limit the use of AI in construction projects.
AIC5	AI Challenges / Human-AI Relationship	39. Ethical concerns, such as data privacy, should be considered when using AI.
AIC6	AI Challenges / Human-AI Relationship	40. AI should support engineers and project managers rather than replace them.

APPENDIX C: SPSS / EXCEL CODING PLAN

The Google Forms response file was exported to Excel and coded for statistical analysis. The following coding plan was used to prepare the dataset. Composite means were calculated by averaging the relevant coded items for each construct.

Table C.1 Response Coding Plan

Variable Name	Description	Coding / Calculation
respondent_id	Sequential numeric identifier	1, 2, 3, ...
job_position	Current job position	Text categories
work_area	Main area of work	Text categories
experience	Years of experience	Text categories
project_type	Main project type	Text categories
ai_tool_use	Use/dealing with AI tools	Yes / No / Not sure
ai_knowledge	Knowledge level about AI	Very Low to Very High
AIA1–AIA8	AI Adoption items	1–5 Likert
CPP1–CPP10	Construction Project Performance items	1–5 Likert
DME1–DME10	Decision-Making Efficiency items	1–5 Likert
AIC1–AIC6	AI Challenges items	1–5 Likert
AIA_Mean	Composite AI Adoption score	Mean of AIA1–AIA8
CPP_Mean	Composite Construction Project Performance score	Mean of CPP1–CPP10
DME_Mean	Composite Decision-Making Efficiency score	Mean of DME1–DME10
AIC_Mean	Composite AI Challenges score	Mean of AIC1–AIC6
main_benefits / main_challenges / replace_view	Open-ended responses	Text

The coding plan in Table C.1 provides the variable names, labels, and composite-score rules required to reproduce the analysis in SPSS or Excel.

APPENDIX D: SUPPLEMENTARY STATISTICAL OUTPUT

This appendix provides supplementary statistical output notes, formulas, and syntax summaries that support the statistical analysis reported in Chapter Four. The purpose of this appendix is to make the analysis more transparent and to provide the supervisor or examiner with additional details if official SPSS output is requested later.

Analysis Component	Purpose	Key Output from the Study
Reliability analysis	Assess internal consistency of the questionnaire constructs	All Cronbach's Alpha values were above 0.85; total scale alpha was 0.960.
Descriptive statistics	Describe the perceived level of each construct	All construct means were in the high range.
Pearson correlation	Assess the strength and direction of relationships	All main construct relationships were positive and statistically significant.
Regression analysis	Test predictive effect of AI Adoption and related constructs	AI Adoption significantly predicted both project performance and decision-making efficiency.
Exploratory indirect-effect analysis	Assess whether the observed regression paths are consistent with an indirect pathway	The Sobel test was significant; causal mediation was not established.
One-sample test	Test whether respondents agreed that AI supports rather than replaces engineers	The AI-support item was significantly above the neutral value of 3.

Table D.1 Supplementary Statistical Output Summary

D.1 Regression Equations Used in Interpretation

The simple regression model for testing the effect of AI Adoption on Construction Project Performance was: $CPP = 0.401 + 0.796(AI \text{ Adoption})$. The positive coefficient indicates that higher perceived AI adoption was associated with higher perceived construction project performance.

The regression model for testing the effect of AI Adoption on Decision-Making Efficiency was: $DME = 0.476 + 0.844(AI \text{ Adoption})$. This model had the highest R-square value among the simple models, confirming that AI adoption was strongly associated with decision-making efficiency.

The regression model for testing the effect of Decision-Making Efficiency on Construction Project Performance was: $CPP = 0.899 + 0.685(DME)$. This result supports the conceptual argument that better decisions are associated with stronger project performance.

The combined model including AI Adoption and Decision-Making Efficiency explained 54.3% of the variance in Construction Project Performance. Both predictors remained statistically significant, and the exploratory Sobel test was consistent with a possible indirect pathway through decision-making efficiency. Because the study was cross-sectional and did not use bootstrapped confidence intervals, this result does not establish causal mediation or confirm direct and indirect causal effects.

Table D.2 SPSS Syntax Summary

Table D.2 summarizes the principal SPSS procedures corresponding to the analyses reported in Chapter Four.

SPSS Command	Purpose
FREQUENCIES	Generate demographic counts and percentages.
DESCRIPTIVES	Calculate means and standard deviations for items and composite scores.
RELIABILITY /SCALE	Calculate Cronbach's Alpha for each measurement construct.
CORRELATIONS	Generate Pearson correlations among AI Adoption, CPP, DME, and AI Challenges.
REGRESSION	Test hypotheses by estimating predictor effects and R-square values.
T-TEST /TESTVAL=3	Test whether AI-supportive role mean is significantly above neutral.