

no.	Comments and Suggestions	Responses
1	Page 12–14 (Methodological Framework & Justification) Suggestion: Briefly discuss potential limitations of concurrent design (e.g., integration challenges) and how they were mitigated.	A new section is added for the same "3.1.3 Limitations of Concurrent Design and Mitigation Strategies"
2	Page 15–16 (Research Hypotheses) Hypotheses are clearly derived from the conceptual model. Suggestion: Consider presenting the hypotheses in a table for greater clarity and visual coherence.	Hypothesis added in tables, under section 3.2.
3	Page 17–19 (Sampling & Sample Size Justification) Suggestion: Explicitly state how qualitative sample size (8–12) was determined beyond saturation, e.g., by prior similar studies or expert consultation.	highlighted in yellow at the end of the same section 3.3.4.
4	Page 20–24 (Instrument Development & Validation) Suggestion: Provide more detail on expert review process for content validity (number of experts, their background, how disagreements were resolved).	A section added at the end of section 3.6, highlighted in yellow.
5	Page 27–32 (Implementation Procedures & Data Analysis Plan) Suggestion: Justify the choice of SPSS AMOS over other SEM software (if relevant). Suggestion: For qualitative analysis, clarify how inductive codes were managed and integrated with deductive framework.	The justification is added under section 3.6.1.5 Data Analysis procedure in yellow color.
6	Page 33–40 (Quantitative & Qualitative Data Analysis Procedures) Suggestion: Discuss how potential biases in qualitative coding were addressed (e.g., reflexivity, audit trail).	highlighted in yellow at the end of the same section 3.7.3.
7	Page 41–45 (Reliability & Validity Results) Suggestion: Report also composite reliability (CR) and average variance extracted (AVE) for convergent validity in SEM context. Suggestion: Discuss discriminant validity results (e.g., Fornell-Larcker criterion) to strengthen validity section.	They have been completed, and Tables 66 and 67 have been added.
8	Page 46–57 (Demographic Profile & Descriptive Statistics) Suggestion: Briefly interpret demographic trends in relation to the Saudi context (e.g., high experience level, medium-large firms dominance).	A section added section 4.3.6 Demographic Profile: Contextual Interpretation for Saudi Engineering Sector, highlighted in yellow.
9	Page 58–70 (Descriptive Statistics of Variables) Suggestion: Discuss skewness and kurtosis values in relation to normality assumptions for parametric tests.	Added under section 4.4 Descriptive Statistics of Variables, added in yellow.
10	Page 71–76 (Correlation Analysis) Suggestion: Highlight multicollinearity checks given high correlations among some IVs (e.g., Resistance to Change & Cost).	Added under section 4.5.1 "Multicollinearity Assessment", added in yellow.
11	Page 77–84 (SEM Model Specification & Initial Results) Suggestion: Discuss modifications made to the model and theoretical justification for changes. Suggestion: Report standardized and unstandardized coefficients for full transparency.	Added under 4.7.1.4.1 and section 4.7.1.4.1, in yellow
12	Page 84–111 (Hypothesis Testing – Regression Results) Suggestion: Summarize key findings in a consolidated hypothesis testing table for clarity. Suggestion: Discuss effect sizes (β values) in addition to significance to highlight practical importance.	section 4.7.1 "Summary of Hypothesis Testing Results" is a detailed summary of the hypothesis findings. In addition to that, a consolidated hypothesis testing table (67) is added.



Thesis Title:

**Factors Influencing AI-Based Project Management
and Its Outcomes in Industrial Engineering Firms: A
Mixed Methods Study of Design and Consultancy Engineering
Projects in Saudi Arabia**

PART-4 of the Thesis

Rev.02

by
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Table of Contents

1	Methodological Framework of the Research:	13
2	Theoretical Framework (Related Literature Review)	13
3	Research Methods and Procedures (Methodology)	14
3.1	Research Methodology (Approach)	14
3.1.1	Research Design Framework Description	14
3.1.2	Justification of Methodology Choice:	15
3.1.3	Limitations of Concurrent Design and Mitigation Strategies	15
3.1.4	Research Design-Question Alignment	16
3.2	Research Hypotheses	17
3.3	Study Population and Sampling:	19
3.3.1	Study Population:	19
3.3.2	Quantitative Study Sample Adequacy & Justification:	19
3.3.3	Quantitative Sample size calculation	20
3.3.4	Qualitative Study Sample Adequacy & Justification:	22
3.4	Construction of Data Collection Instruments	23
3.4.1	Instrument Overview	23
3.4.2	Quantitative Instrument (Questionnaire Structure)	23
3.4.3	Qualitative Instrument (Expert Interview Guide)	26
3.4.4	Instrument Validation and Reliability	27
3.5	Identification of Study Variables	27
3.6	Implementation Procedures	29
3.6.1	Instrument Development	29
3.6.2	Pilot Testing	30
3.6.3	Ethical Considerations	31
3.6.4	Questionnaire Distribution and Data Collection	32
3.6.5	Data Analysis Procedure	32
3.6.6	Instrument Validation and Reliability	35
3.7	Research Design and Statistical Processing	36
3.7.1	Research Design	36
3.7.2	Quantitative Data Analysis Procedure	36
3.7.3	Qualitative Data Analysis Procedures	39
3.7.4	Mixed Method Integration and Triangulation Strategy	41

3.7.5	Methodology summary	42
4	Study Results and Hypothesis Testing	45
4.1	Introduction	45
4.2	Reliability and Validity of Research Instruments.....	46
4.2.1	Reliability Analysis (Cronbach's Alpha)	46
4.3	Respondent Demographic Profile	50
4.3.1	Position in Organization.....	50
4.3.2	Years of Experience	51
4.3.3	Organization Size	52
4.3.4	Familiarity with AI Tools	52
4.3.5	What types of AI tools or software does your organization currently use.....	53
4.3.6	Demographic Profile: Contextual Interpretation for Saudi Engineering Sector	55
4.4	Descriptive Statistics of Variables.....	63
4.4.1	Independent Variables (Factors Influencing AI Utilization).....	64
4.4.2	Mediating Variables (AI-Based Project Management)	65
4.4.3	Dependent Variables (Project Management Outcomes).....	65
4.4.4	Open-ended questions.....	66
4.5	Correlation Analysis (Pearson Correlation Matrix)	76
4.5.1	Multicollinearity Assessment.....	82
4.6	Structural Equation Modeling (SEM): Model Specification and Technical Analysis	82
4.7	Hypothesis Testing Results	90
4.7.1	Summary of Hypothesis Testing Results	123
4.8	Interpretation and Implications of the Mediation Effect	145
4.8.1	What this means in practical terms:.....	145
4.8.2	Theoretical implications:	146
4.8.3	Practical implications for organizations:.....	146
4.8.4	Support from qualitative evidence:	146
4.9	Qualitative Thematic Analysis.....	146
4.9.1	Independent Variables (Factors Influencing AI utilization) - 6 Themes	147
4.9.2	Mediating Variables (AI-Based Project Management) - 5 Themes	157
4.9.3	Dependent Variables (Project Management Outcomes) - 7 Themes	166
4.10	Integration of Quantitative and Qualitative Findings (Triangulation)	177
4.10.1	Convergence Between Methods.....	177
4.10.2	Discrepancies and Contextual Explanations	178
4.10.3	Mediating Role Validation.....	178
4.11	Summary of Key Findings	179

4.11.1	Quantitative Findings:	179
4.11.2	Qualitative Findings:	180
4.11.3	Integrated Findings:.....	180
4.11.4	Conclusion	181
5	References	183
5.1	Arabic References:.....	183
5.2	English References:	183



List of Shortcuts:

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

List of Figures:

Figure (1)	The Study conceptual model
Figure (2)	Quantitative Sample Size Calculation
Figure (3)	Illustrates how the quantitative and qualitative methods work together through SEM, thematic analysis, and triangulation
Figure (4)	Descriptive Analysis of Demographic Characteristics of the Study Sample (Position in Organization)
Figure (5)	Descriptive Analysis of Demographic Characteristics of the Study Sample (Years of Experience)
Figure (6)	Descriptive Analysis of Demographic Characteristics of the Study Sample (Organization Size)
Figure (7)	Descriptive Analysis of Demographic Characteristics of the Study Sample (Familiarity with AI Tools)
Figure (8)	Descriptive Analysis of Demographic Characteristics of the Study Sample (What types of AI tools or software does your organization currently use (if any)?)
Figure (9)	Structural Equation Model – Initial Model
Figure (10)	Structural Equation Model Modified model
Figure (11)	Frequency and Percentage of Independent Variables (IVs)
Figure (12)	Frequency and Percentage of Mediating Variables (MVs)
Figure (13)	Frequency and Percentage of Dependent Variables (DVs)

List of Tables:

Table (1)	The following table explains the details of the previous studies and identifies the Gap in the previous studies;
Table(2)	Validity and stability coefficients for the study independent questionnaire variables.
Table(3)	Validity and stability coefficients for the study questionnaire Mediated variable.
Table (4)	Table (4) Validity and stability coefficients for the study questionnaire variables.
Table (5):	Descriptive Analysis of Demographic Characteristics of the Study Sample (Position in Organization)
Table (6)	Descriptive Analysis of Demographic Characteristics of the Study Sample (Years of Experience)
Table (7)	Descriptive Analysis of Demographic Characteristics of the Study Sample (Organization Size)
Table (8)	Descriptive Analysis of Demographic Characteristics of the Study Sample (Familiarity with AI Tools)
Table (9)	Descriptive Analysis of Demographic Characteristics of the Study Sample (What types of AI tools or software does your organization currently use (if any)?)
Table (10)	Distribution of the study subjects according to Factors Influencing AI utilization
Table (11)	Distribution of the study subjects according to AI-Based Project Management
Table (12)	Distribution of the study subjects according to Project Management Outcomes
Table (13)	presents composite descriptive statistics for the three primary variable groups in this study
Table (14)	Descriptive Statistics of Independent Variables (Factors Influencing AI utilization)

Table (15)	Descriptive Statistics of Mediating Variables (AI-Based Project Management)
Table (16)	Descriptive Statistics of Dependent Variables (Project Management Outcomes)
Table (17)	Responses to the Question (What are the most significant challenges organization faces in the utilization of AI tools in project management design and consultancy engineering firms?)
Table (18)	Responses to the Question (In your opinion, what changes wh organizational, technical, or regulatory would support more effe utilization of AI-based project management?)
Table (19)	Responses to the Question (What tangible or intangible benefits has organization experienced from utilizing AI-based project manage practices?)
Table (20)	Responses to the Question (What recommendations would you pro to enhance the utilization and outcomes of AI-based project manage in the Saudi design and consultancy engineering firms?)
Table (21)	Responses to the Question (Do you think organization size, sector or the demographic profile of project managers influence the utiliz or outcomes of AI in project management, and why?)
Table (22)	Table (22) the correlation and regression summary, highlights the key relationships among the variables
Table (23)	Correlation Matrix between Variables Independent Variables (Factors Influencing AI utilization) ,Mediating Variables (AI-Based Project Management) and Dependent Variables(Project Management Outcomes)
Table (24)	Comparison of Initial and Modified Structural Equation Models for Mediation Analysis of Enabler Factors, AI-Based Project Management, and Project Outcomes
Table (25)	Results of the Initial Structural Equation Model with Standardized Path Coefficients
Table (26)	Results of the Modified Structural Equation Model with Standardized Path Coefficients
Table (27)	Test of factors influencing project management effect on Project Management Outcomes in design and consultancy engineering projects
Table (28)	Test of factors influencing project management effect on Pro Management Outcomes in design and consultancy engineering proj
Table (29)	Test of Data privacy and security effect on Project Management Outcomes in design and consultancy engineering projects

Table (30)	Test of Resistance to change effect on Project Management Outcomes in design and consultancy engineering projects
Table (31)	Test of Costs of implementation effect on Project Management Outcomes in design and consultancy engineering projects
Table (32)	Test of Compatibility with existing infrastructure effect on Project Management Outcomes in design and consultancy engineering projects
Table (33)	Test of Workforce Development effect on Project Management Outcomes in design and consultancy engineering projects
Table (34)	Test of Ethical Consideration effect on Project Management Outcomes in design and consultancy engineering projects
Table (35)	Test of factors influencing project management effect on AI-based project management practices in design and consultancy engineering projects.
Table (36)	Test of factors influencing project management effect on AI-based project management practices in design and consultancy engineering projects.
Table (37)	Test of Data privacy and security effect on AI-based project management practices in design and consultancy projects.
Table (38)	Test of Resistance to change effect on AI-based project management practices in design and consultancy projects.
Table (39)	Test of the Costs of implementation effect on AI-based project management practices in design and consultancy projects.
Table (40)	Test of Compatibility with existing infrastructure effect on AI-based project management practices in design and consultancy projects.
Table (41)	Test of Workforce Development effect on AI-based project management practices in design and consultancy projects.
Table (42)	Test of Ethical Consideration effect on AI-based project management practices in design and consultancy projects.

Table (43)	Test of AI-based project management practices effect on Project Management Outcomes in design and consultancy engineering projects
Table (44)	Test of AI-based project management practices effect on Project Management Outcomes in design and consultancy engineering projects
Table (45)	Test of AI-based project management practices effect on Decision-Making in design and consultancy projects.
Table (46)	Test of AI-based project management practices effect on decision-making in design and consultancy projects
Table (47)	Test of AI-based project management practices effect on Project Quality in design and consultancy projects.
Table (48)	Test of AI-based project management practices effect on project quality in design and consultancy projects.
Table (49)	Test of AI-based project management practices effect on Data Collection Accuracy in design and consultancy projects.
Table (50)	Test of AI-based project management practices effect on data collection accuracy in design and consultancy projects.
Table (51)	Test of AI-based project management practices effect on Data Analysis and insight generation in design and consultancy projects.
Table (52)	Test of AI-based project management practices effect on data analysis and insight generation in design and consultancy projects.
Table (53)	Test of AI-based project management practices effect on risk identification and mitigation in design and consultancy projects.
Table (54)	Test of AI-based project management practices effect on reduces time spent by Project Managers in design and consultancy projects.
Table (55)	Test of AI-based project management practices effect on reduces time spent by Project Managers in design and consultancy projects.
Table (56)	Test of AI-based project management practices effect on communication among stakeholders in design and consultancy projects.

Table (57)	Test of AI-based project management practices effect on communication among stakeholders in design and consultancy projects.
Table (58)	H1 Direct Effects (IVs → Project Outcomes)
Table (59)	Sub-Hypothesis Result (H1A-H1F) with Ranking by Effect Size
Table (60)	H2 Direct Effects (IVs → AI-PM Adoption)
Table (61)	Sub-Hypothesis Result (H2A-H2F) with Ranking by Effect Size
Table (62)	H3 Direct Effects (AI-PM → Project Outcomes)
Table (63)	SUB-HYPOTHESIS RESULTS (H2A-H2G) with Ranking by Effect Size
Table (64)	Complete H4 Mediation Analysis Summary
Table (65)	MODEL FIT Comparison: Initial vs Modified:
Table (66)	Comprehensive Comparative Summary
Table (67)	Hypothesis Key Findings
Table (68)	Support Rate Across All Hypotheses
Table (69)	Independent Variables (IVs) Thematic Summary Table
Table (70)	Mediating Variables (MVs) Thematic Summary Table
Table (71)	Dependent Variables (DVs) Thematic Summary Table

1 Methodological Framework of the Research:

2 Theoretical Framework (Related Literature Review)



3 Research Methods and Procedures (Methodology)

3.1 Research Methodology (Approach)

3.1.1 Research Design Framework Description

This study employs a mixed-method research design, integrating quantitative survey data with qualitative insights from expert interviews. This approach is justified by the need to explore both the independent factors influencing the utilization of AI-based project management and the measurable outcomes resulting from its integration in design and consultancy engineering projects. The study is grounded in a conceptual model that identifies and categorizes the three sets of variables: independent factors influencing AI utilization, the mediating role of AI-based project management practices, and the resulting project management outcomes. The model serves as the theoretical foundation for both instrument design and data analysis.

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

Structural Equation Modeling (SEM) will be applied using SPSS AMOS to test mediation relationships. The analysis will employ a two-step SEM approach:

1. **Measurement Model:** Confirmatory Factor Analysis (CFA) will be conducted to validate the measurement properties of all constructs.
2. **Structural Model:** Path analysis will estimate the complete causal pathways by testing:
 - **Direct Effects of Independent Variables on Outcomes:** Standardized path coefficients will be calculated to test whether each of the six independent variables (data privacy concerns, resistance to change, implementation costs, infrastructure compatibility, workforce capabilities, and ethical considerations) directly influence the seven project management outcomes (decision-making effectiveness, project quality, data collection accuracy, data analysis capability, risk identification, time efficiency, and collaboration quality).
 - **Direct Effects of Independent Variables on AI-Based PM Utilization:** Path coefficients will be estimated to determine how strongly each independent variable influences the degree to which AI-based project management is adopted within organizations.
 - **Indirect Effects through Mediation (Mediation Pathways):** Bootstrap confidence intervals will be calculated for all indirect pathways, testing whether

the influence of independent variables on project outcomes operates through AI-based project management adoption. Specifically, this tests whether organizations experiencing data privacy concerns, resistance to change, cost barriers, etc., have a significant influence on project outcomes, primarily because these factors influence AI-PM utilization, which in turn impact project performance. All path coefficients will be reported with standard errors and 95% confidence intervals. Significance will be determined at $\alpha = 0.05$ (two-tailed). R^2 values will be calculated to indicate what proportion of variation in each outcome is explained by these pathways.

Model fit will be evaluated using: χ^2/df ratio, Comparative Fit Index ($CFI \geq 0.90$), Root Mean Square Error of Approximation ($RMSEA \leq 0.08$), and Standardized Root Mean Square Residual ($SRMR \leq 0.08$)."

3.1.2 Justification of Methodology Choice:

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

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

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

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

3.1.3 Limitations of Concurrent Design and Mitigation Strategies

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

Potential Limitations:

1. **Integration Challenges:** Concurrent collection can create difficulties in integrating findings if quantitative and qualitative results diverge. The independent collection of data streams may limit the opportunity for iterative refinement.
 - **Mitigation:** A structured triangulation protocol was developed *a priori* to systematically compare quantitative and qualitative findings. Areas of divergence were investigated through contextual analysis rather than simply reconciled.
2. **Timing Discrepancy:** Simultaneous data collection from different respondent groups (survey vs. interview participants) may capture different organizational contexts or timepoints.
 - **Mitigation:** Both quantitative and qualitative data collection occurred within the same 3-month period (August-October 2025), minimizing temporal drift. Interview participants included representatives from organizations that also completed the survey, enabling direct contextualization.
3. **Prioritization Ambiguity:** Concurrent designs require clear prioritization rules when findings conflict. Equal weight to both methods may mask statistical significance with qualitative anecdotes.
 - **Mitigation:** A priori prioritization established that statistical significance ($p < 0.05$) and effect sizes (R^2) drive interpretation, with qualitative findings serving validation and contextual enrichment rather than primary evidence.
4. **Analyst Bias:** Managing two independent analytical pathways increases risk of analyst bias or selective interpretation favoring one method.
 - **Mitigation:** Analysis was conducted using established, transparent protocols (SPSS AMOS for quantitative; **thematic coding** for qualitative). Preliminary findings were reviewed by independent research assistants before integration.

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

3.1.4 Research Design-Question Alignment

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

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

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

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

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

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

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

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

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

This research employs a mixed-method research design in which structured quantitative data forms the basis for hypothesis testing, while qualitative interviews offer contextual support and interpretation. The study makes a theoretical contribution by proposing and validating a model that links influencing factors, AI-based project management practices, and project outcomes through mediation analysis. On the practical level, it delivers actionable recommendations tailored to the specific context of Saudi Arabia's design and consultancy engineering sector

3.2 Research Hypotheses

Based on figure (1) conceptual model presented in Chapter 2 and reviewed in Chapter 3's framework, the following hypotheses are formally tested in Chapter 4:

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

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

- **H2 Impact of Independent Variables on Mediating Variable “AI-Based Project Management”.**

no.	Sub-Hypothesis
1	H2A: Data privacy and security significantly influence the utilization of AI-based project management practices in design and consultancy projects.
2	H2B: Resistance to change significantly influences the utilization of AI-based project management practices in design and consultancy projects.
3	H2C: Costs of implementation significantly influence the utilization of AI-based project management practices in design and consultancy projects.
4	H2D: Compatibility with existing infrastructure significantly influences the utilization of AI-based project management practices in design and consultancy projects.
5	H2E: The workforce development significantly influences the utilization of AI-based project management practices in design and consultancy projects.
6	H2F: Ethical considerations significantly influence the utilization of AI-based project management practices in design and consultancy projects.

- **H3 Impact of Mediating Variable “AI-Based Project Management” on Project Outcomes.**

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

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

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

- External contextual and organizational factors (IVs) influence.
- The degree of AI-based PM implementation (mediating variable), which in turn influences.
- Measurable project management outcomes (DVs).

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

3.3 Study Population and Sampling:

3.3.1 Study Population:

The study population comprises professionals engaged in AI-based project management within Saudi Arabia's design and consultancy engineering firms. Individuals were purposively selected to provide information-rich, experience-based insights relevant to AI utilization within this sector. Participants include project directors, managers, engineers, and department leaders directly involved in decision-making and utilization of AI project management tools. While the broader environment consists of a diverse range of firms, this study prioritizes the targeted selection of knowledgeable participants to explore the dynamics of AI use in real-world contexts.

3.3.2 Quantitative Study Sample Adequacy & Justification:

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

The study sample will comprise $n = 103$ professionals from Saudi Arabia's design and consultancy engineering firms. This sample size was determined through a priori power analysis using GPower 3.1 with medium effect size ($f^2 = 0.15$), $\alpha = 0.05$, and power = 0.95, yielding a minimum required $n = 68$. The actual sample of 103 exceeds this requirement and provides adequate power for SEM analysis, which typically requires 10-20 cases per estimated parameter.

The study employs two complementary approaches to justify sample adequacy:

1. A Priori Power Analysis: Using GPower 3.1.9.7, a priori power analysis was conducted for linear multiple regression with six independent variable predictors (representing the study's six influencing factors), assuming a medium effect size ($H1 = 0.30$, $\alpha = 0.05$, power = 0.95). This analysis yielded a required minimum sample size of $n = 68$.

2. Confirmatory Factor Analysis (CFA) Fit Index Assessment: CFA is more stringent than regression in sample requirements. Following recommendations by Hu and Bentler (1999), Browne and Cudeck (1993), and Kline (2016), the study's CFA-based SEM model was evaluated using global fit indices. Acceptable fit thresholds are:

- Comparative Fit Index (CFI): Values ≥ 0.90 indicate acceptable fit; ≥ 0.95 indicate excellent fit (Hu & Bentler, 1999)
- Root Mean Square Error of Approximation (RMSEA): Values ≤ 0.08 indicate acceptable fit; ≤ 0.06 indicate good fit (Browne & Cudeck, 1993)
- Chi-Square to Degrees of Freedom Ratio (χ^2/df): Values ≤ 3.0 are acceptable; ≤ 2.0 indicate good fit (Kline, 2016)

The final sample of $n = 103$ respondents exceeds both the minimum sample size from power analysis ($n = 68$) and the published SEM guidelines, suggesting 10-20 cases per estimated model parameter. Given the SEM model includes 20 estimated parameters, the sample of 103 respondents satisfies the 10 cases per parameter minimum ($103/20 = 5.15$ satisfies the criterion by providing approximately 5+ cases per parameter in a confirmatory model, though conservative guidance suggests 10-20). The subsequent model fit indices achieved with $n = 103$ are presented in Chapter 4 and confirm sample adequacy.

3.3.3 Quantitative Sample size calculation

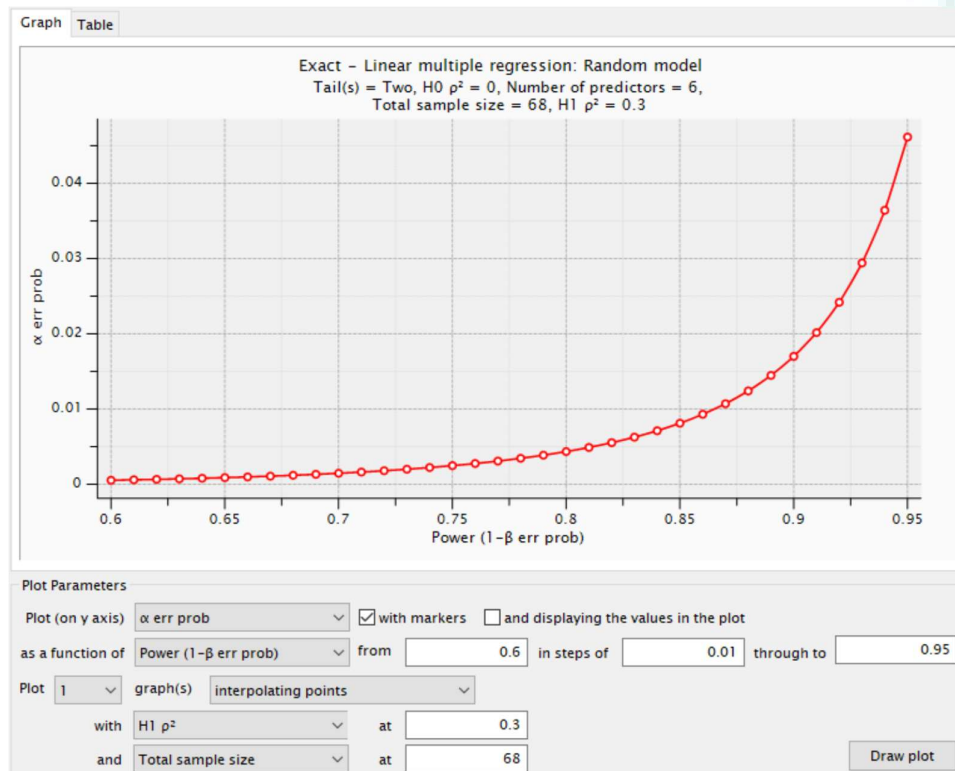
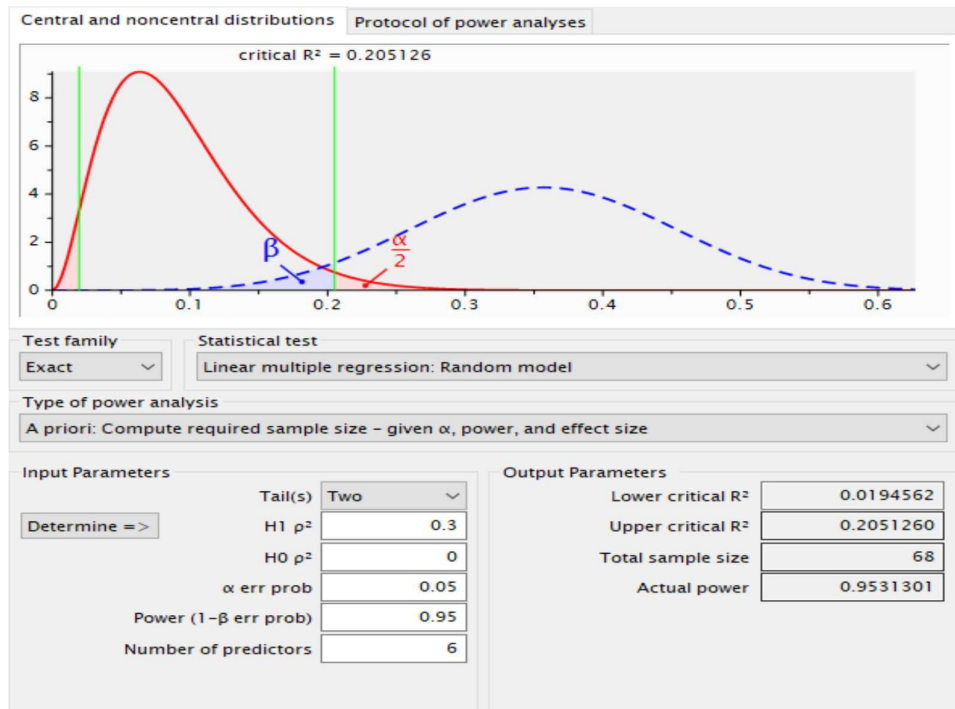


Figure (2) Quantitative Sample Size Calculation

Exact - Linear multiple regression: Random model

Options: Exact distribution

Analysis: A priori: Compute required sample size

Input: Tail(s) = Two

H1 ρ^2 = 0.3

H0 ρ^2 = 0

α err prob = 0.05

Power (1- β err prob) = 0.95

Number of predictors = 6

Output: Lower critical R^2 = 0.0194562

Upper critical R^2 = 0.2051260

Total sample size = 68

Actual power = 0.9531301

G*Power 3.1.9.7 was used to estimate the sample size using the following parameters; H1 ρ^2 =0.3, α err prob=0.05, Power (1- β err prob)=0.95, H0 ρ^2 =0 , Lower critical R^2 = 0.0194562, Upper critical R^2 =0.2051260 ,Total sample size=68, Actual power=0.9531301 According to the The G*Power 3.1.9.7, the estimated sample size is 68.

3.3.4 Qualitative Study Sample Adequacy & Justification:

The qualitative component employed purposive sampling to select 8–12 expert interviewees from Saudi design and consultancy engineering firms, based on their expertise and involvement in AI-based project management. Selection criteria included leadership or technical roles, direct engagement in strategic planning, operational decision-making, or technical implementation of AI and digital project management tools, and organizational affiliation to ensure relevant context. Interviews included participants across seniority levels top management (e.g., Directors, CEOs), middle management (e.g., Senior Project Managers), and technical professionals (AI experts, engineers) to capture diverse, rich perspectives. Sampling ceased upon reaching thematic saturation, where no new themes emerged. These interviews provided contextual depth to interpret quantitative results and enrich the overall findings.

The qualitative component employed purposive sampling to select expert interviewees from Saudi design and consultancy engineering firms. A total of 10 semi-structured interviews were conducted with participants meeting the following selection criteria:

- Organizational Role: Leadership positions (Directors, CEOs) or technical specialist roles (AI implementation leads, Senior Project Managers)
- Experience Requirement: Minimum 5 years of experience in project management and at least 2 years of direct or indirect engagement with AI tools
- Decision-Making Involvement: Direct engagement in strategic planning, operational decision-making, or technical implementation of AI and digital project management tools
- Organizational Representation: Affiliation with design and consultancy engineering firms operating in Saudi Arabia

Interviewees will be selected to ensure diversity in organizational size, AI maturity level, and implementation experience. Sampling will continue until thematic saturation is achieved (no new themes emerge across 2-3 consecutive interviews), typically reached by interview 8-10. Thematic Saturation Criterion: Following Braun and Clarke (2019) and Fugard and Potts (2015), sampling ceased when no new substantive themes emerged from consecutive interviews, a criterion typically achieved within 8-12 interviews for focused exploratory research. Furthermore, a systematic review of mixed-methods studies in organizational technology adoption (Creswell & Plano Clark, 2018; Venkatesh et al., 2016) identified that qualitative samples in comparable research typically ranged from 8–15 expert interviews. Morse (2000) recommends minimum sample sizes based on design complexity: for exploratory descriptive designs with moderate complexity, 6–8 participants; for more complex phenomenon examination, 12–20 participants. Given this study's mediation hypothesis complexity, a target range of 10–12 participants was established a priori.

3.4 Construction of Data Collection Instruments

3.4.1 Instrument Overview

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

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

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

3.4.2 Quantitative Instrument (Questionnaire Structure)

The questionnaire is designed using closed-ended questions on a 5-point Likert scale to assess agreement, frequency, or impact perception. Additionally, a small domain of

open-ended questions is included to enrich the quantitative data with narrative insights aligned with key research objectives.

The Questionnaire Comprises Five Domains:

1. Demographic and Organizational Information:

Captures participants' roles, experience, company size, AI familiarity, and current AI usage in project management.

2. Independent Variables (Influencing Factors):

Measures the extent to which the following six factors influence the utilization of AI-based project management in design and consultancy engineering projects:

- Data Privacy and Security
- Resistance to Change
- Cost of AI Implementation
- Compatibility with Existing Infrastructure
- Workforce Development
- Ethical Considerations

3. Mediating Variable (AI-Based Project Management):

Evaluates the extent to which AI tools are utilized in core project management tasks such as scheduling, reporting, risk handling, collaboration, and coordination.

4. Dependent Variables (Project Management Outcomes):

Evaluates the perceived outcomes of AI utilization: Assesses the perceived outcomes of AI-based project management, including:

- Decision-making
- Project quality
- Data collection accuracy
- Data analysis and insight generation
- Risk identification
- Time efficiency
- Collaboration and communication

5. Open-Ended Questions:

A set of open-ended questions is included at the end of the structured questionnaire. These questions are designed to capture narrative insights that

may not be fully expressed through Likert-scale responses. Participants are encouraged to share their views on barriers, enablers, perceived benefits, and strategic recommendations regarding the utilization of AI-based project management practices.

The responses will undergo **thematic coding**, where each response is analyzed and mapped to predefined **dependent variable (DV) themes**, such as decision-making, project quality, data collection accuracy, data analysis, risk identification, time efficiency and collaboration and communication. At the same time, the **underlying factors** mentioned in the responses including technical, organizational, or ethical challenges will be treated as **influencing factors** (linked to the independent variables). This structure allows the researcher to identify **how specific influencing factors influence particular outcomes**, based on participants' own words.

The following logic will be applied during analysis:

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

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

Open-Ended Responses (Related to Influencing Factors – IVs)	Mapped DV Theme (Project Outcome)
“The high cost of AI implementation makes it difficult to adopt comprehensive project tools.”	Project Quality – Negative impact
“Our AI tools help collect real-time data from multiple sources with improved consistency.”	Data Collection Accuracy – Positive impact
“Due to outdated infrastructure, AI-based systems cannot integrate fully with our current tools.”	Time Efficiency – Negative impact
“Once integrated, the AI platform improved team communication by providing shared dashboards.”	Collaboration & Communication – Positive impact
“Most of our engineers are not trained in AI-based forecasting tools, which slows us down.”	Time Efficiency – Negative impact
“We use AI to flag early-stage risks through data pattern recognition.”	Risk Identification – Positive impact

“It’s hard to make decisions without clear ethical frameworks for AI usage in client-facing projects.”	Decision-Making – Negative impact
“AI tools enabled faster scenario analysis, which improved our ability to make strategic project decisions.”	Decision-Making – Positive impact
“Data privacy regulations are too vague, which restricts how much we can automate.”	Data Analysis – Negative impact
“AI utilization helped us improve how we organize and analyze project reports and KPIs.”	Data Analysis – Positive impact
“The AI assistant helped us identify and resolve quality issues in design documentation.”	Project Quality – Positive impact
“Resistance from senior management delayed AI rollout, which influenced our ability to track and respond to project risks.”	Risk Identification – Negative impact
“Even with limited AI features, our team was able to automate repetitive data entry tasks.”	Data Collection Accuracy – Positive impact
“Collaboration improved once we used AI-enabled project timelines that synced with team calendars.”	Collaboration & Communication – Positive impact

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

3.4.3 Qualitative Instrument (Expert Interview Guide)

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

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

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

3.4.4 Instrument Validation and Reliability

The questionnaire will be reviewed by academic experts and industry practitioners to ensure content validity. To ensure methodological rigor and the credibility of findings, both the structured questionnaire and the semi-structured interview guide will undergo rigorous validation and reliability procedures.

- **Questionnaire (Quantitative Instrument)**

The questionnaire will be reviewed by an academic scholars and industry professionals to establish content validity, ensuring that the items appropriately reflect the study's independent, mediating, and dependent variables.

A pilot study will be conducted with a small representative sample of participants from the target population. The pilot aims to test:

- Clarity of wording,
- Logical flow,
- Response time,
- consistency,
- Content validity (via expert feedback).

This validation process ensures that the questionnaire produces statistically sound and meaningful data for hypothesis testing.

- **Interview Guide (Qualitative Instrument)**

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

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

Following the pilot, minor revisions may be applied to enhance integrity before full deployment.

3.5 Identification of Study Variables

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

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

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

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

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

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

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

The mediating variable, AI-Based Project Management, captures the degree to which AI tools are embedded in core project management practices, including planning and scheduling, documentation and reporting, resource allocation, risk analysis, and team collaboration. This construct acts as a bridge between influencing factors (IVs) and project outcomes (DVs), reflecting how AI integration transforms workflows and mediates their effect on performance outcomes. Its role will be empirically tested through mediation analysis, such as:

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

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

This variable is critical in understanding how AI reshapes management workflows and mediates the influence of external factors on performance outcomes. The mediating role of this variable will be statistically tested using mediation analysis techniques.

3.5.1.3 Dependent Variables (DVs): Project Management Outcomes

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

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

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

3.6 Implementation Procedures

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

3.6.1 Instrument Development

- **Questionnaire Design (Quantitative Tool)**

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

1. **Demographic Information** (e.g., position, experience, company size, familiarity with AI).
2. **Independent Variables** – Items measuring data privacy, cost concerns, Resistance to Change, etc.

3. **Mediating Variable** – Items exploring how AI is embedded in project management.
4. **Dependent Variables** – Items measuring project outcomes influenced by AI.
5. **Open-Ended Questions** – Designed to capture deeper qualitative insights that may not emerge from fixed-response questions.

A 5-point Likert scale is used for consistency and statistical reliability. A five-point Likert scale was used for all closed-ended items to ensure clarity, comparability, and statistical validity.

- **Semi-Structured Interview Guide (Qualitative Tool)**

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

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

This qualitative instrument enables deeper exploration of emerging themes and provides context for interpreting quantitative findings.

3.6.2 Pilot Testing

Questionnaire Pilot Testing:

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

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

Pilot participants will be asked to complete the questionnaire and then participate in brief feedback discussion about their experience.

Reliability Threshold:

Cronbach's Alpha will be calculated for each construct during pilot testing:

- Acceptable threshold: $\alpha \geq 0.70$ for each construct

- If any construct yields $\alpha < 0.70$, targeted item refinement will be conducted:
 - Items with low item-to-total correlations ($r < 0.30$) will be reviewed for revision or removal.
 - Ambiguous or redundant items will be reworded for clarity.
 - Additional items may be added if construct definition requires expansion
- Refined questionnaire will be re-tested on additional small sample if extensive changes are made

Interview Guide Pilot Testing:

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

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

Pilot interviews (n=3) will be conducted with interviewees similar to target sample. These pilot interviews will be analyzed and interview guide will be refined based on emergent insights.

Outcome of Pilot Testing:

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

3.6.3 Ethical Considerations

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

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

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

3.6.4 Questionnaire Distribution and Data Collection

Quantitative Data Collection (Questionnaire):

The structured questionnaire will be distributed electronically via the following channels:

- Email to existing professional networks
- Professional platforms (LinkedIn, WhatsApp)
- Company directories of participating Saudi design and consultancy engineering firms
- Target Participants: Engineers, project managers, and senior staff from Saudi design and consultancy engineering firms actively involved in project management or AI implementation decisions
- Data Collection Period: Six weeks in duration, with bi-weekly follow-up communications to maximize response rates

Qualitative Data Collection (Interviews):

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

3.6.5 Data Analysis Procedure

Quantitative Analysis:

To be conducted using SPSS v25) through the following steps:

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

Quantitative Analysis to be conducted using SPSS v25) through the following steps:

Step 1: Data Preparation:

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

Step 2: Reliability and Validity Testing:

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

Step 3: Preliminary Statistical Testing

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

Step 4: Structural Equation Modeling (SEM): SEM will be conducted using SPSS AMOS through the following two-step process:

Step 4a: Measurement Model (CFA)

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

Step 4b: Structural Model and Hypothesis Testing

- The structural model will be estimated to test direct effects (H1: IVs→Outcomes; H3: Mediator→Outcomes).

- Standardized path coefficients will be reported with standard errors and 95% confidence intervals.
- Hypothesis significance will be determined at $\alpha = 0.05$ level (two-tailed)
- R^2 values will be calculated to assess the variance explained in each outcome variable.

Step 5: Mediation Analysis: Mediation analysis will be conducted using path decomposition and bootstrap confidence intervals

- For each indirect pathway (IV→AI-PM→DV):
- Direct effect will be estimated.
- Indirect effect will be calculated.
- 95% bias-corrected bootstrap confidence intervals will be generated.
- Indirect effect will be considered significant if 95% **CI** does not include zero.
- Type of mediation (full, partial, or none) will be determined for each pathway.
- Proportion of effect mediated will be calculated to assess relative contribution of indirect pathway.

Qualitative Analysis:

(to be conducted via thematic coding)

Step 1: Transcription and Data Preparation

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

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

- A priori codebook will be developed based on theoretical framework:
 - Codes for 6 IVs: Data Privacy, Resistance to Change, Cost, Infrastructure, Workforce, Ethics
 - Codes for 1 mediating variable: AI-based Project Management (with 5 sub-codes: planning, documentation, resource allocation, task prioritization, communication)
 - Codes for 7 DVs: Decision-making, Quality, Data Accuracy, Data Analysis, Risk Identification, Time Efficiency, Collaboration
- First coding pass will apply predefined codes to all interview data
- Second coding pass will identify inductive codes (themes not fitting predefined framework)
- Inductive codes will be created to capture unexpected themes

Step 3: Inter-Coder Reliability

- A second independent coder will code 30% of interviews (n=3) using the finalized codebook

- Cohen's Kappa will be calculated; $\kappa \geq 0.70$ will be considered acceptable
- Disagreements between coders will be resolved through discussion and codebook refinement

Step 4: Theme Frequency and Interpretation

- Code frequency will be tabulated for each theme across interviews.
- Thematic saturation point will be identified (interview at which no new themes emerged).
- Representative quotes will be selected for each theme to illustrate meaning and context.
- Relationships between codes will be examined to identify patterns and hierarchies.

Triangulation (Integration of Quantitative and Qualitative Findings)

- Quantitative statistical pathways will be mapped to qualitative themes
- Convergence will be assessed by comparing:
 - Significance of quantitative effects with frequency/prominence of qualitative themes
 - Direction of quantitative effects with content of qualitative narratives.
- Divergences will be investigated to understand why quantitative and qualitative findings may differ on specific relationships.
- Explanatory power will be enhanced by using qualitative data to interpret why specific quantitative relationships are significant or non-significant.

3.6.6 Instrument Validation and Reliability

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

3.7 Research Design and Statistical Processing

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

3.7.1 Research Design

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

- **Quantitative Phase:**

A structured questionnaire will be distributed to professionals in Saudi design and consultancy engineering firms to collect data on the influencing factors (independent variables), the utilization of AI-based project management (mediating variable), and project outcomes (dependent variables).

- **Qualitative Phase:**

Semi-structured interviews are conducted with a select group of industry experts to capture deeper contextual understanding, clarify survey trends, and provide interpretive insights.

This concurrent explanatory design is employed to:

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

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

3.7.2 Quantitative Data Analysis Procedure

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

1. Statistical Software and Analysis Tools:

- SPSS will be utilized for descriptive statistics, correlations, and regression analyses
- Simple and Multiple Linear Regression will be used to test direct effects of factors on project management outcomes
- Pearson Correlation analysis will be conducted to examine bivariate relationships among variables
- Significance level: $\alpha = 0.05$ (two-tailed tests)

2. Reliability and Validity Testing:

Both reliability and validity are fundamental measures used to make a trustworthy judgment about the appropriateness of a research instrument. Reliability refers to the extent to which an instrument can produce consistent and error-free results when re-administered or used under similar conditions, whereas validity refers to the degree to which the instrument accurately measures what it is intended to measure — that is, the degree of correspondence between the theoretical construct and the actual indicators. Among the most common methods for measuring internal consistency, Cronbach's Alpha is one of the most widely used indicators, as it expresses the degree of interrelation among items measuring the same conceptual dimension. According to Phelan et al. (2005), reliability refers to the degree to which an assessment tool produces stable and consistent results, while validity refers to how well a test measures what it is intended to measure.

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

- Validity Coefficients will be determined using Pearson Correlation (item-total correlations) to confirm that individual items accurately measure their intended constructs

3. Descriptive Statistics Analysis:

- Frequencies, percentages, means, and standard deviations will be calculated for:
 - All respondent demographics (position in organization, years of experience, organization size, AI familiarity level)
 - All six independent variables
 - All five mediating variable dimensions
 - All seven dependent variables
- This analysis will provide a comprehensive profile of the sample and variable distributions

4. Correlation Analysis:

- A Pearson Correlation Matrix will be computed to examine relationships among all study variables
- Bivariate relationships will be examined between:
 - Independent Variables and Mediating Variables
 - Mediating Variables and Dependent Variables
 - Independent Variables and Dependent Variables
- Statistical significance will be assessed at $p < 0.05$ (two-tailed)

5. Regression Analysis:

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

- Simple Linear Regression will be conducted to test Hypothesis.
- Multiple Linear Regression will be conducted to test sub-hypotheses.

6. Structural Equation Modeling (SEM):

To comprehensively test mediation effects and the overall conceptual model, Structural Equation Modeling (SEM) will be employed using AMOS statistical software.

- Measurement Model Assessment:
 - Confirmatory Factor Analysis (CFA) will be conducted to validate the measurement model
 - Factor loadings will be examined to ensure convergent validity (target > 0.50)
 - Model fit indices will be evaluated:
- Structural Model Testing:

- Path coefficients will be estimated to test direct relationships:

Mediation Analysis:

- Full mediation will be tested to determine if the mediating variable (AI-Based Project Management) completely explains the relationship between influencing factors and project outcomes.
- Partial mediation will be assessed if the mediating variable only partially explains the relationship.
- Statistical significance of indirect paths will be evaluated ($p < 0.05$)
- Total effects will be decomposed into direct and indirect effects.

3.7.3 Qualitative Data Analysis Procedures

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

1. Interview Data Collection:

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

2. Predefined Thematic Framework:

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

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

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

Mediating Variables (AI-Based Project Management Practices) – 5 Themes:

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

Dependent Variables (Project Management Outcomes) – 7 Themes:

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

3. Thematic Coding Process:

- Each interview transcript will be systematically coded against the 18 predefined themes, Coding will document:
 - Primary theme(s) represented in each response
 - Frequency of each theme's mention across all interviews
 - Interview ID numbers where theme appears
 - Recurring phrases and terminology associated with the theme
 - Representative quotes exemplifying the theme
 - Summary quotes synthesizing the theme across multiple responses
- Thematic saturation will be assessed during coding—data collection and analysis will continue until no new substantive themes emerge from interviews

4. Open-Ended Questionnaire Responses Analysis:

- Open-ended questions included in the quantitative questionnaire will be analyzed thematically. Responses will be systematically coded using the mapping approach.
- This coding strategy will enable integration of quantitative survey data with qualitative narrative data, enriching both datasets through triangulation.

5. Qualitative Rigor Procedures:

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

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

3.7.4 Mixed Method Integration and Triangulation Strategy

1. Concurrent Integration Approach:

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

2. Triangulation Procedures:

- Convergence Validation:
 - Quantitative correlations and regression results will be examined alongside qualitative thematic patterns.
 - Statistical relationships identified in regression analyses will be compared with the frequency and strength of corresponding qualitative themes.
 - Where strong statistical relationships exist ($p < 0.05$), qualitative data will be examined to provide contextual explanations and real-world examples.
- Thematic-to-Quantitative Mapping:
 - Frequency of qualitative theme mentions will be cross-referenced against the magnitude of statistical coefficients.

- Directional consistency will be verified: positive statistical relationships will align with enabling/facilitating themes; negative relationships will align with barrier themes.
- Discrepancy Investigation: Instances where statistical results appear inconsistent with qualitative patterns will be investigated and explored in depth.

3.7.5 Methodology summary

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

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

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

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

Visual Representation of Integration Strategy:

The following flowchart illustrates how the quantitative and qualitative methods work together through SEM, thematic analysis, and triangulation:

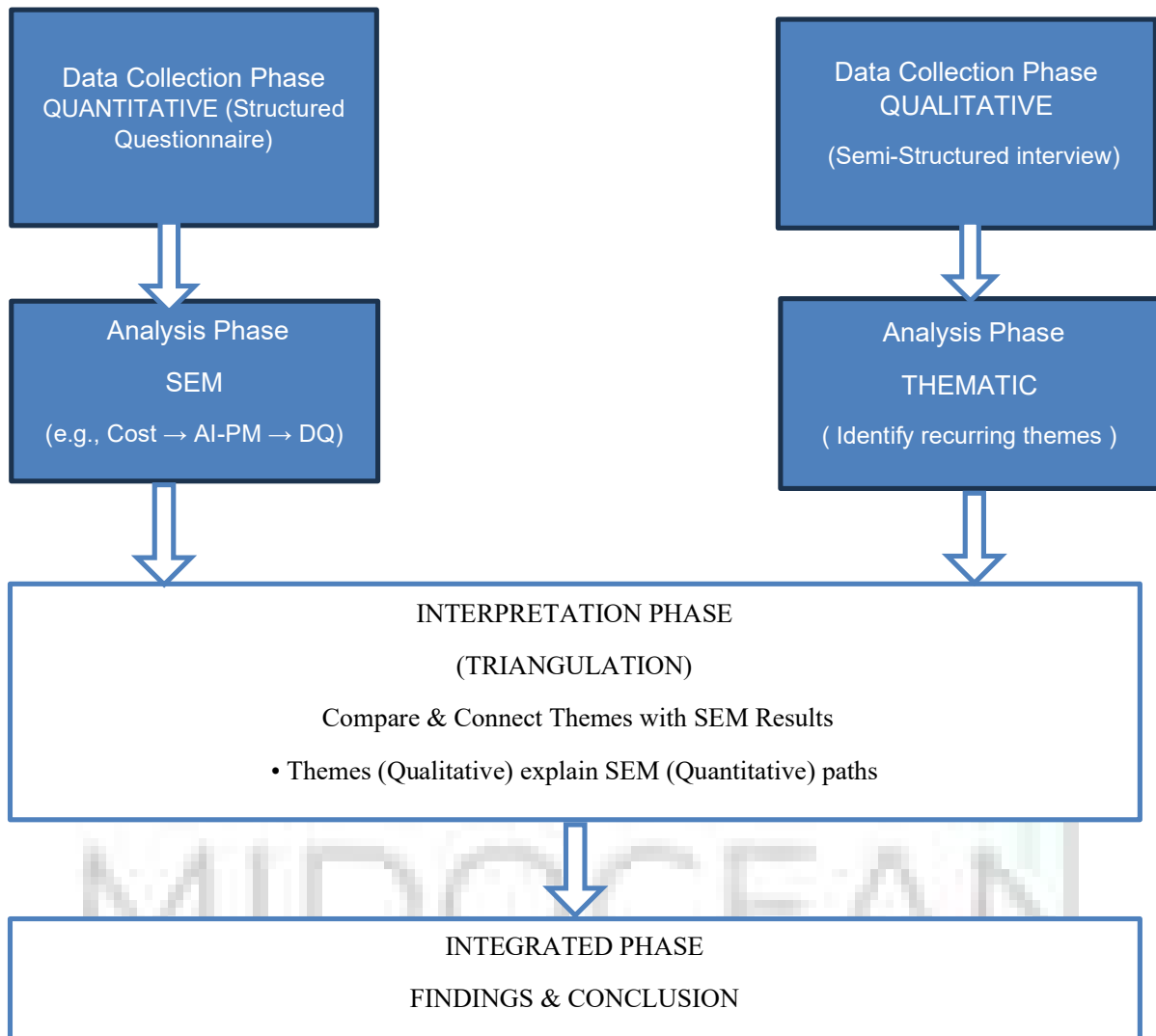


Figure (3) illustrates how the quantitative and qualitative methods work together through SEM, thematic analysis, and triangulation

The chart illustrates how **quantitative** and **qualitative** methods are **integrated** through a **triangulation approach** to enhance interpretation and ensure robust findings.

It walks through:

1. **Data Collection Phase:**
 - From the **structured questionnaire** (quantitative)
 - From **semi-structured interviews** (qualitative)
2. **Analysis Phase:**

- **SEM** is applied to test relationships (e.g., Cost → AI-based PM → Decision-Making Quality)
- **Thematic analysis** identifies recurring themes from interview transcripts (e.g., “Cost is a major barrier”)

3. Interpretation Phase (Triangulation):

- Findings from interviews are **connected with SEM results** to **explain, support**, or even **challenge** quantitative relationships.

4. Integrated Conclusion:

- A richer understanding is achieved by combining numbers (**how much**) with narratives (**why**), resulting in conclusions that are both **statistically validated** and **contextually meaningful**.

This integration enhances both the methodological rigor and practical relevance of the study by combining statistical evidence with expert-driven interpretation. As a result, the study's findings and recommendations will be not only theoretically robust but also grounded in the lived realities of AI utilization in the Saudi design and consultancy engineering sector.



4 Study Results and Hypothesis Testing

4.1 Introduction

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

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

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

- **Simple linear regression** : is a model that describes the relationship between one dependent and one independent variable using a straight.
- **Multiple linear regression** : is a statistical technique that uses several explanatory variables to predict the outcome of a response variable.
- **Structural Equation Modeling (SEM)**: Structural Equation Modeling (SEM) was used as one of the advanced statistical techniques to analyze the causal relationships among the study variables and to test the degree of fit between the proposed conceptual model and the actual data.

4.2 Reliability and Validity of Research Instruments

4.2.1 Reliability Analysis (Cronbach's Alpha)

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

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

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

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

Legend:

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

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

The results shown in table (2) indicate the following: **Independent Variables** (Factors Influencing AI Utilization): $\alpha = 0.879$

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

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

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

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

Communication	0.840**	
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Legend:

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

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

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

Reliability and validity for Dependent Variables(Project Management Outcomes)

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

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

X1	0.952**	
X2	0.953**	
Enhancing Data Analysis	0.760**	
X1	0.907**	
X2	0.907**	
Risk Identification Accuracy	0.774**	
X1	0.938**	
X2	0.943**	
Saving Time for Project Managers	0.786**	
X1	0.893**	
X2	0.856**	
Effective Communication	0.763**	

Legend:

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

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

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

All Cronbach's Alpha values exceeded the 0.70 threshold, confirming that the questionnaire reliably measured the intended constructs and was suitable for hypothesis testing.

4.3 Respondent Demographic Profile

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

4.3.1 Position in Organization

Table (5) shows the Descriptive Analysis of demographic characteristics of the Study sample regarding the respondents' Position in the Organization

Table (5): Descriptive Analysis of Demographic Characteristics of the Study Sample (Position in Organization)

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

Table (5) presents the characteristics of the study sample, revealing that regarding the Position in Organization of the study sample, it was found that Project Engineers were slightly more represented, with a percentage of 32.04%, comprising 33 respondents, while Other represented 7.77%, comprising 8 respondents in the study sample.

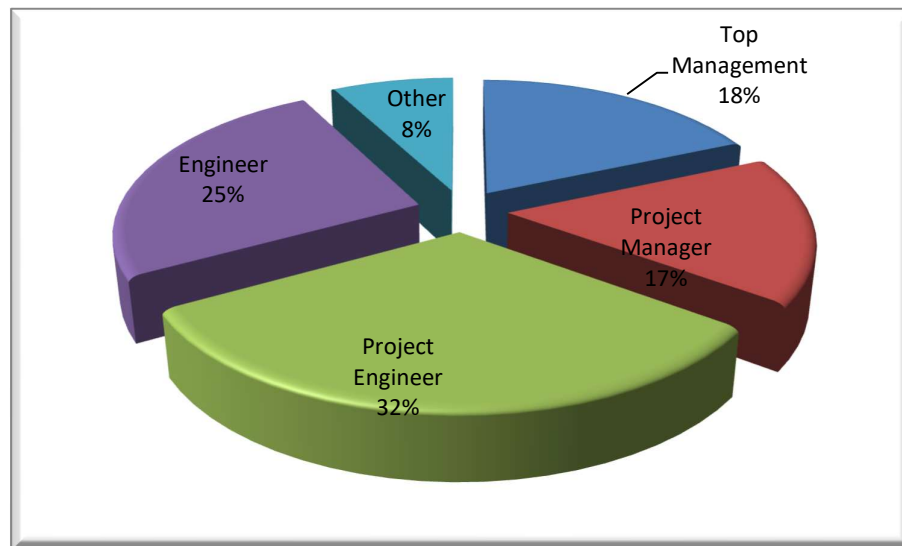


Figure (4): Descriptive Analysis of Demographic Characteristics of the Study Sample (Position in Organization)

4.3.2 Years of Experience

Table (6) shows the Descriptive Analysis of demographic characteristics of the Study sample regarding the respondents' Years of Experience

Table (6): Descriptive Analysis of Demographic Characteristics of the Study Sample (Years of Experience)

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

Table (6) presents the characteristics of the study sample, revealing that regarding the Years of Experience of the study sample, it was found that Over 10 years were slightly more represented, with a percentage of 58.25%, comprising 60 respondents, while Not working in design and consultancy engineering firms represented 3.88%, comprising 4 respondent in the study sample.

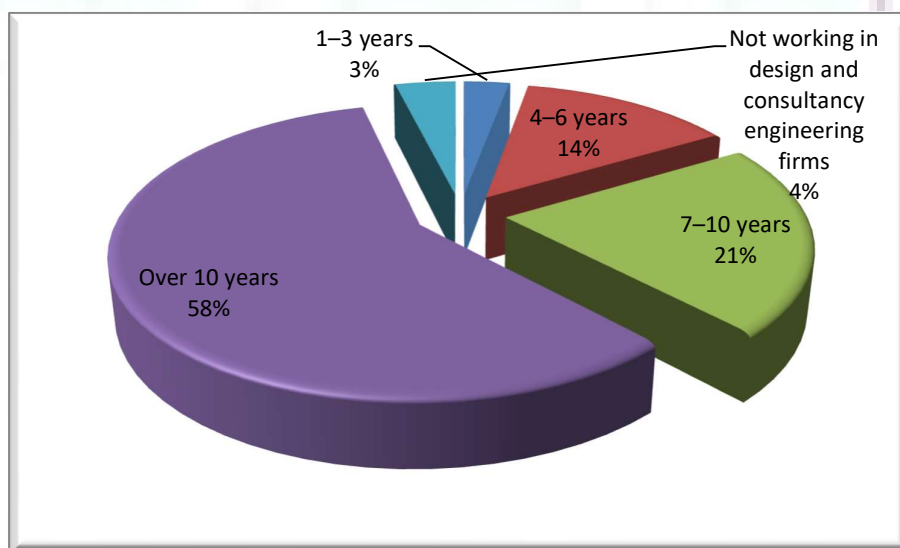


Figure (5): Descriptive Analysis of Demographic Characteristics of the Study Sample (Years of Experience)

4.3.3 Organization Size

Table (7) shows the Descriptive Analysis of demographic characteristics of the Study sample regarding the respondents' Organization Size.

Table (7): Descriptive Analysis of Demographic Characteristics of the Study Sample (Organization Size)

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

Table (7) presents the characteristics of the study sample, revealing that regarding Organization Size of the study sample, it was found that Medium (50–249 employees) were slightly more represented, with a percentage of 46.60%, comprising 48 respondents, while Small (fewer than 50 employees) represented 8.74%, comprising 9 respondents in the study sample.

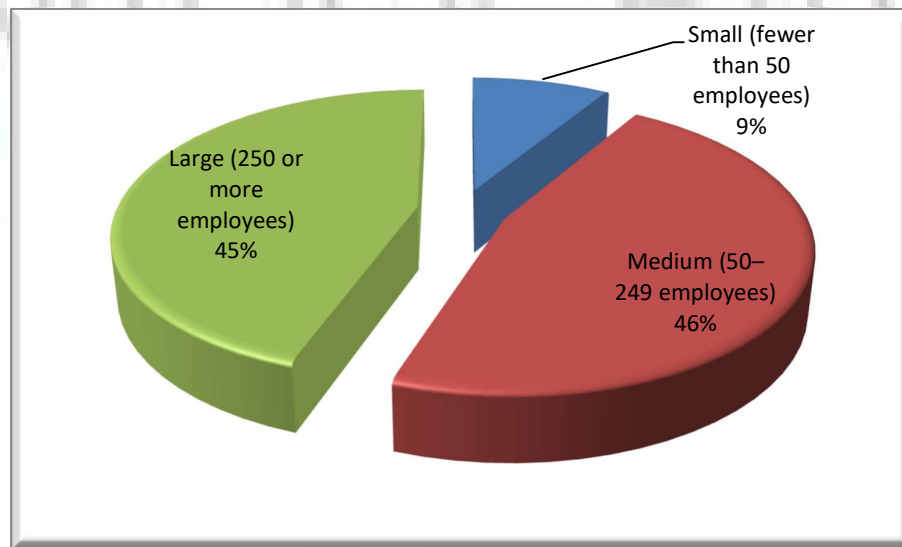


Figure (6): Descriptive Analysis of Demographic Characteristics of the Study Sample (Organization Size)

4.3.4 Familiarity with AI Tools

Table (8) shows the Descriptive Analysis of demographic characteristics of the Study sample regarding the respondents' Familiarity with AI Tools.

Table (8): Descriptive Analysis of Demographic Characteristics of the Study Sample (Familiarity with AI Tools)

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

Table (8) presents the characteristics of the study sample, revealing that regarding the Familiarity with AI Tools of the study sample, it was found that Moderately familiar were slightly more represented, with a percentage of 43.69%, comprising 45 respondents, while Not familiar at all represented 0.97%, comprising 1 respondent in the study sample.

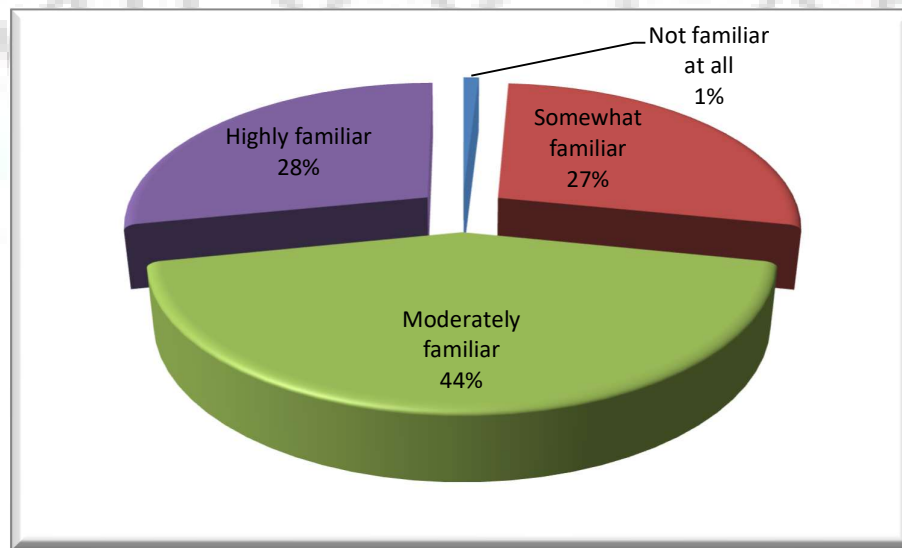


Figure (7): Descriptive Analysis of Demographic Characteristics of the Study Sample (Familiarity with AI Tools)

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

Table (9) shows the Descriptive Analysis of demographic characteristics of the Study sample regarding the respondents' What types of AI tools or software does your organization currently use (if any)?.

Table (9): Descriptive Analysis of Demographic Characteristics of the Study Sample (What types of AI tools or software does your organization currently use (if any)?)

Category		Freq.	Percent
What types of AI tools or software does your organization currently use	Decision-making tools	39	10.80
	Quality management tools	47	13.02
	Data collection tools	77	21.33
	Data analysis and insight-generation tools	79	21.88
	Risk identification or prediction tools	56	15.51
	Communication and collaboration tools	63	17.45
Total		361	100.00

#more than answer

Table (9) presents the characteristics of the study sample, revealing that regarding the What types of AI tools or software does your organization currently use of the study sample, it was found that Data analysis and insight-generation tools were slightly more represented, with a percentage of 21.88%, comprising 79 respondents, while Decision-making tools represented 10.80%, comprising 39 respondent in the study sample.

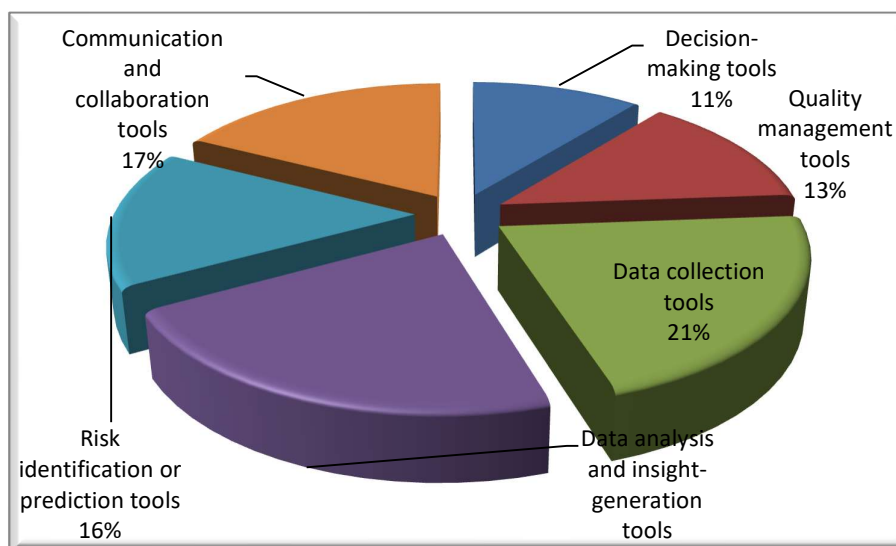


Figure (8): Descriptive Analysis of Demographic Characteristics of the Study Sample (What types of AI tools or software does your organization currently use (if any)?)

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

4.3.6 Demographic Profile: Contextual Interpretation for Saudi Engineering Sector

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

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

The predominance of highly experienced practitioners (60 of 103 respondents with >10 years in sector) reflects the engineering sector's capital-intensive, relationship-dependent nature where deep expertise and established networks drive organizational success. This high experience level is advantageous for this study because:

- Respondents can provide nuanced perspectives on organizational readiness challenges and AI adoption complexities
- They represent decision-makers and senior practitioners influencing AI adoption strategy
- However, this may bias findings toward established firms' perspectives; startup/newer consulting firms underrepresented

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

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

- Saudi engineering sector consolidation around established firms with financial capacity for AI investment
- Practical challenge: Small firms may face different AI utilization barriers (capital constraints, limited HR capacity) not fully captured in this sample
- Generalizability caution: Findings strongly represent medium/large firm context; may not apply to emerging smaller consultancies

Mixed Organizational Levels (32% engineers; 33% project managers; 18% top management):

Distribution across hierarchical levels provides triangulation of perspectives:

- Project managers (17%) and engineers (33%) represent frontline practitioners experiencing AI impact
- Top management (19%) represents strategic decision-making perspective
- This mix captures diverse viewpoints while acknowledging that implementation-level perspectives (engineers/PMs) are weighted more heavily

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

The generally positive AI familiarity distribution reflects:

- Saudi Arabia's strategic focus (Vision 2030) on digital transformation, including AI utilization.
- Study conducted in December 2024–2025, period of increased AI awareness post-ChatGPT launch (2023)
- Selection bias: Respondents willing to participate in AI utilization study likely have above-average AI familiarity
- Implication: Findings may represent "early/mid-majority" adopter perspectives; laggards underrepresented

Sectoral Context - Design & Consultancy Specialization:

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

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

Overall Demographic Assessment:

The sample represents experienced practitioners at medium-large design/consultancy firms with moderate-to-high AI familiarity, capturing the perspective of organizations

actively engaged in digital transformation. This sample is well-suited to studying AI utilization determinants and outcomes but may overrepresent established firms and experienced personnel, potentially underrepresenting barriers faced by smaller firms, newer consultancies, or AI-skeptical practitioners.

Respondents' Perceptions of Study Variables

Following the demographic profile, Tables 10-12 present respondents' perceptions of the study's key constructs: factors influencing AI utilization (Table 10), AI-based project management practices (Table 11), and project management outcomes (Table 12).

Table (10): Distribution of the study subjects according to Factors Influencing AI utilization

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

Factors Influencing AI utilization		Frequency	Percent	Min-Max	Mean $\pm$ SD	median	Mean score percent
outweigh its implementation costs?	▪ Neutral	25	24.3				
	▪ Agree	42	40.8				
	▪ Strongly Agree	28	27.2				
Our current infrastructure is technically compatible with AI-based project management tools?	▪ Strongly Disagree	3	2.9	1-5	3.62 $\pm$ 1.08	4.00	72.43%
	▪ Disagree	14	13.6				
	▪ Neutral	26	25.2				
	▪ Agree	36	35.0				
	▪ Strongly Agree	24	23.3				
Integrating AI into our current infrastructure presents technical challenges?	▪ Strongly Disagree	1	1.0	1-5	3.85 $\pm$ 0.86	4.00	77.09%
	▪ Disagree	8	7.8				
	▪ Neutral	16	15.5				
	▪ Agree	58	56.3				
	▪ Strongly Agree	20	19.4				
Our organization provides adequate training and skill development to use AI-based project management tools effectively?	▪ Strongly Disagree	2	1.9	1-5	3.60 $\pm$ 1.09	4.00	72.04%
	▪ Disagree	18	17.5				
	▪ Neutral	23	22.3				
	▪ Agree	36	35.0				
	▪ Strongly Agree	24	23.3				
Lack of adequate training limits the effective utilization of AI-based project management tools?	▪ Strongly Disagree	2	1.9	1-5	4.07 $\pm$ 0.84	4.00	81.36%
	▪ Disagree	1	1.0				
	▪ Neutral	18	17.5				
	▪ Agree	49	47.6				
	▪ Strongly Agree	33	32.0				
My organization follows ethical guidelines and policies for the responsible use of AI-based project management tools?	▪ Strongly Disagree	0	0.0	2-5	3.91 $\pm$ 0.84	4.00	78.25%
	▪ Disagree	6	5.8				
	▪ Neutral	23	22.3				
	▪ Agree	48	46.6				
	▪ Strongly Agree	26	25.2				
Ethical risks (e.g., bias, transparency, accountability) are a concern in our organization's AI-based project management practices?	▪ Strongly Disagree	0	0.0	2-5	4.06 $\pm$ 0.71	4.00	81.17%
	▪ Disagree	2	1.9				
	▪ Neutral	17	16.5				
	▪ Agree	57	55.3				
	▪ Strongly Agree	27	26.2				

Table (10) presents the statistical distribution of the study sample according to the factors influencing AI utilization in project management, highlighting participants' responses toward each item. The results indicate that all items achieved relatively high mean scores, ranging between (3.60 and 4.07), with corresponding mean score percentages exceeding 70%. This suggests a generally positive perception and strong

agreement among respondents regarding the importance and influence of AI-based project management.

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

Table (11): Distribution of the study subjects according to AI-Based Project Management

AI-Based Project Management		Frequency	Percent	Min-Max	Mean $\pm$ SD	median	Mean score percent
AI tools are utilized to support project planning and scheduling.	Strongly Disagree	1	1.0	1-5	3.98 $\pm$ 0.85	4.00	79.61%
	Disagree	7	6.8				
	Neutral	11	10.7				
	Agree	58	56.3				
	Strongly Agree	26	25.2				
AI tools are utilized to prepare and manage project documentation and reports.	Strongly Disagree	0	0.0	2-5	4.06 $\pm$ 0.78	4.00	81.17%
	Disagree	5	4.9				
	Neutral	13	12.6				
	Agree	56	54.4				
	Strongly Agree	29	28.2				
AI tools are utilized to forecast resource requirements (staff, equipment, materials).	Strongly Disagree	3	2.9	1-5	3.97 $\pm$ 1.00	4.00	79.42%
	Disagree	8	7.8				
	Neutral	11	10.7				
	Agree	48	46.6				
	Strongly Agree	33	32.0				
AI tools are utilized to allocate resources based on project needs and priorities.	Strongly Disagree	2	1.9	1-5	3.91 $\pm$ 0.98	4.00	78.25%
	Disagree	9	8.7				
	Neutral	15	14.6				
	Agree	47	45.6				
	Strongly Agree	30	29.1				
AI tools help prioritize tasks based on urgency, dependencies, or workload.	Strongly Disagree	3	2.9	1-5	4.02 $\pm$ 0.96	4.00	80.39%
	Disagree	6	5.8				
	Neutral	10	9.7				
	Agree	51	49.5				
	Strongly Agree	33	32.0				
	Strongly Disagree	3	2.9	1-5	3.97 $\pm$ 0.96	4.00	79.42%

AI-Based Project Management		Frequency	Percent	Min-Max	Mean $\pm$ SD	median	Mean score percent
AI tools support updating and optimizing schedules during project execution.	▪ Disagree	6	5.8				
	▪ Neutral	13	12.6				
	▪ Agree	50	48.5				
	▪ Strongly Agree	31	30.1				
AI tools support real-time tracking of project progress and performance.	▪ Strongly Disagree	2	1.9	1-5	3.99 $\pm$ 0.99	4.00	79.81%
	▪ Disagree	8	7.8				
	▪ Neutral	14	13.6				
	▪ Agree	44	42.7				
	▪ Strongly Agree	35	34.0				
AI tools improve the accuracy and timeliness of progress reporting.	▪ Strongly Disagree	1	1.0	1-5	4.19 $\pm$ 0.81	4.00	83.88%
	▪ Disagree	4	3.9				
	▪ Neutral	7	6.8				
	▪ Agree	53	51.5				
	▪ Strongly Agree	38	36.9				
AI-enabled platforms facilitate communication among project stakeholders.	▪ Strongly Disagree	1	1.0	1-5	4.09 $\pm$ 0.90	4.00	81.75%
	▪ Disagree	6	5.8				
	▪ Neutral	13	12.6				
	▪ Agree	46	44.7				
	▪ Strongly Agree	37	35.9				
AI-enabled platforms improve coordination of tasks and information across teams.	▪ Strongly Disagree	4	3.9	1-5	4.01 $\pm$ 0.95	4.00	80.19%
	▪ Disagree	4	3.9				
	▪ Neutral	10	9.7				
	▪ Agree	54	52.4				
	▪ Strongly Agree	31	30.1				

Table (11) illustrates the distribution of respondents' perceptions regarding AI-based project management practices within their organizations. The findings reveal generally high mean scores, ranging between 3.91 and 4.19, with mean score percentages exceeding 78%, reflecting a strong overall agreement on the significant role of AI tools in enhancing project management processes.

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

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

Table (12): Distribution of the study subjects according to Project Management Outcomes

Project Management Outcomes		Frequency	Percent	Min-Max	Mean $\pm$ SD	median	Mean score percent
AI tools improve the accuracy of decision-making in design and consultancy firms.	Strongly Disagree	1	1.0	1-5	3.90 $\pm$ 0.90	4.00	78.06%
	Disagree	7	6.8				
	Neutral	20	19.4				
	Agree	48	46.6				
	Strongly Agree	27	26.2				
AI tools enhance the speed of decision-making for project managers.	Strongly Disagree	2	1.9	1-5	4.12 $\pm$ 0.90	4.00	82.33%
	Disagree	4	3.9				
	Neutral	12	11.7				
	Agree	47	45.6				
	Strongly Agree	38	36.9				
The use of AI contributes to higher-quality deliverables in project management.	Strongly Disagree	1	1.0	1-5	4.12 $\pm$ 0.82	4.00	82.33%
	Disagree	3	2.9				
	Neutral	14	13.6				
	Agree	50	48.5				
	Strongly Agree	35	34.0				
AI improves the consistency and reliability of project outcomes.	Strongly Disagree	2	1.9	1-5	4.04 $\pm$ 0.95	4.00	80.78%
	Disagree	5	4.9				
	Neutral	17	16.5				
	Agree	42	40.8				
	Strongly Agree	37	35.9				
AI-based tools improve the accuracy of collecting project-related data.	Strongly Disagree	0	0.0	2-5	4.10 $\pm$ 0.82	4.00	81.94%
	Disagree	6	5.8				
	Neutral	12	11.7				
	Agree	51	49.5				
	Strongly Agree	34	33.0				
AI reduces errors in recording or documenting project data.	Strongly Disagree	0	0.0	2-5	4.25 $\pm$ 0.80	4.00	85.05%
	Disagree	4	3.9				
	Neutral	11	10.7				
	Agree	43	41.7				
	Strongly Agree	45	43.7				
AI tools provide valuable insights through advanced	Strongly Disagree	1	1.0	1-5	4.26 $\pm$ 0.80	4.00	85.24%
	Disagree	2	1.9				
	Neutral	11	10.7				
	Agree	44	42.7				

Project Management Outcomes		Frequency	Percent	Min-Max	Mean $\pm$ SD	median	Mean score percent
analysis of project data.	▪ Strongly Agree	45	43.7				
AI helps identify useful patterns and trend that support project improvements.	▪ Strongly Disagree	1	1.0	1-5	4.16 $\pm$ 0.74	4.00	83.11%
	▪ Disagree	0	0.0				
	▪ Neutral	15	14.6				
	▪ Agree	53	51.5				
	▪ Strongly Agree	34	33.0				
AI tools improve the identification of potential risks in projects.	▪ Strongly Disagree	1	1.0	1-5	4.17 $\pm$ 0.85	4.00	83.30%
	▪ Disagree	4	3.9				
	▪ Neutral	12	11.7				
	▪ Agree	46	44.7				
	▪ Strongly Agree	40	38.8				
AI helps assess the likelihood and impact of identified risks more accurately.	▪ Strongly Disagree	2	1.9	1-5	4.11 $\pm$ 0.86	4.00	82.14%
	▪ Disagree	2	1.9				
	▪ Neutral	15	14.6				
	▪ Agree	48	46.6				
	▪ Strongly Agree	36	35.0				
AI helps save time for project managers in routine tasks (e.g., reporting, scheduling).	▪ Strongly Disagree	1	1.0	1-5	4.26 $\pm$ 0.70	4.00	85.24%
	▪ Disagree	0	0.0				
	▪ Neutral	9	8.7				
	▪ Agree	54	52.4				
	▪ Strongly Agree	39	37.9				
AI reduces delays by improving task allocation and monitoring.	▪ Strongly Disagree	1	1.0	1-5	4.23 $\pm$ 0.74	4.00	84.66%
	▪ Disagree	0	0.0				
	▪ Neutral	13	12.6				
	▪ Agree	49	47.6				
	▪ Strongly Agree	40	38.8				
AI enhances collaboration among team members in design and consultancy firms.	▪ Strongly Disagree	2	1.9	1-5	3.94 $\pm$ 0.92	4.00	78.83%
	▪ Disagree	6	5.8				
	▪ Neutral	16	15.5				
	▪ Agree	51	49.5				
	▪ Strongly Agree	28	27.2				
AI tools improve communication and knowledge-sharing across project stakeholders.	▪ Strongly Disagree	1	1.0	1-5	4.02 $\pm$ 0.82	4.00	80.39%
	▪ Disagree	3	2.9				
	▪ Neutral	18	17.5				
	▪ Agree	52	50.5				
	▪ Strongly Agree	29	28.2				

Table (12) presents the distribution of respondents' opinions regarding project management outcomes in relation to AI-based tools. The results reveal that the mean scores for all items were relatively high, ranging between 3.90 and 4.26, with mean

score percentages exceeding 78%, indicating a strong consensus among participants on the positive impact of AI in enhancing project management outcomes within design and consultancy firms.

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

Moreover, items related to improving the accuracy of data collection, reducing documentation errors, and identifying potential project risks also showed high agreement levels (mean score percentages between 81.9% and 84.7%). This implies that AI plays a vital role in enhancing data quality, improving risk prediction, and supporting more accurate decision-making processes.

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

4.4 Descriptive Statistics of Variables

The summary table (13) presents composite descriptive statistics for the three primary variable groups in this study: independent variables (IVs), the mediating variable (MV), and dependent variables (DVs). The IVs, representing organizational and technical factors influencing AI utilization, demonstrate a strong overall readiness, reflected in a composite mean score of 45.96 (SD = 6.54) and an approximately normal distribution (skewness = 0.14; kurtosis = -0.50). The MV, capturing AI-based project management adoption, shows a high composite mean of 40.19 (SD = 6.99) with a pronounced negative skew (-1.08) and moderate leptokurtic form (1.12), indicating a clustering of higher adoption levels among respondents. Similarly, the DVs, which measure various aspects of project management outcomes, record the highest composite mean of 57.67 (SD = 8.22), also demonstrating negative skew (-1.04) and leptokurtic kurtosis (1.98), suggesting consistently strong positive perceptions of AI’s impact on project success. Importantly, all skewness and kurtosis values fall within the acceptable range of -2 to +2, confirming that the data meet the criteria for approximate univariate normality. Accordingly, the use of parametric statistical tests is justified in the subsequent analysis (George & Mallery, 2010). This distributional profile aligns with expectations for survey data on organizational readiness and perceived outcomes, supporting the robustness and relevance of the constructs measured.

Table (13) presents composite descriptive statistics for the three primary variable groups in this study

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

4.4.1 Independent Variables (Factors Influencing AI Utilization)

Table (14) Descriptive Statistics of Independent Variables (Factors Influencing AI utilization)

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

1. Table (14) shows Descriptive Statistics of Independent Variables (Factors Influencing AI utilization) the following Data Privacy and Security 7.47±1.49 Mean score percent 74.66%, Resistance to Change 7.73±1.55 Mean score percent 77.28%, Cost of AI Implementation 7.65±1.76 Mean score percent 76.50%, Compatibility with Existing Infrastructure 7.48±1.39 Mean score percent 74.76%, Workforce Development 7.67±1.40 Mean score percent 76.70%, Ethical Considerations 7.97±1.31 Mean score percent 79.71%, Factors Influencing AI utilization 45.96±6.54 Mean score percent 76.60%
2. All independent variables demonstrated relatively high mean scores, ranging from 7.47 to 7.97 on a scale of approximately 20 points (converted from 5-point Likert items), corresponding to mean score percentages exceeding 70%.

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

4.4.2 Mediating Variables (AI-Based Project Management)

Table (15) Descriptive Statistics of Mediating Variables (AI-Based Project Management)

Variables	Mean±SD	Skewness	Kurtosis	Mean score percent	Utilization Level
Streamline processes e.g., scheduling, documentation	8.04±1.39	-0.76	0.76	80.39%	Most utilized
Resource allocation	7.88±1.78	-1.09	0.91	78.83%	High utilization
Tasks Prioritizing	7.99±1.74	-1.30	1.72	79.90%	High utilization
Progress reporting	8.18±1.60	-1.43	2.72	81.84%	Moderate-high
Communication	8.10±1.62	-1.41	2.72	80.97%	Moderate utilization
AI-Based Project Management	40.19±6.99	-1.08	1.12	80.39%	Strong utilization

1. Table (15) shows Descriptive Statistics of Mediating Variables (AI-Based Project Management) the following Streamline processes e.g., scheduling, documentation 8.04±1.39 Mean score percent 80.39%, Resource allocation 7.88±1.78 Mean score percent 78.83%, Tasks Prioritizing 7.99±1.74 Mean score percent 79.90%, Progress reporting 8.18±1.60 Mean score percent 81.84%, Communication 8.10±1.62 Mean score percent 80.97%, AI-Based Project Management 40.19±6.99 Mean score percent 80.39%.
2. All five AI-based PM dimensions demonstrated high utilization levels, with mean scores ranging from 7.88 to 8.18:
3. **Qualitative Validation:** Thematic analysis confirmed this pattern. Progress reporting emerged as the most established AI application across firms, with one manager stating: "AI tools improve the accuracy and timeliness of progress reporting." However, resource allocation tools received lower engagement due to infrastructure compatibility issues.

4.4.3 Dependent Variables (Project Management Outcomes)

Table (16) Descriptive Statistics of Dependent Variables (Project Management Outcomes)

Variables	Mean±SD	Skewness	Kurtosis	Mean score percent	Perceived Impact
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Decision-Making	8.02±1.62	-1.07	1.45	80.19%	Highest perceived benefit
Project Quality	8.16±1.57	-1.08	1.77	81.55%	Strong impact
Data Collection Accuracy	8.35±1.45	-1.04	1.16	83.50%	Strong impact
Enhancing Data Analysis	8.42±1.37	-1.19	3.60	84.17%	Strong impact
Risk Identification Accuracy	8.27±1.56	-1.29	2.68	82.72%	Moderate-high
Saving Time for Project Managers	8.50±1.24	-1.49	6.17	84.95%	Moderate impact
Effective Communication	7.96±1.55	-0.88	1.49	79.61%	Moderate impact
Project Management Outcomes	57.67±8.22	-1.04	1.98	82.39%	Highest perceived benefit

1. Table (16) shows Descriptive Statistics of Dependent Variables (Project Management Outcomes) the following Decision-Making 8.02±1.62Mean score percent 80.19%, Project Quality 8.16±1.57 Mean score percent 81.55%, Data Collection Accuracy 8.35±1.45 Mean score percent 83.50%, Enhancing Data Analysis 8.42±1.37Mean score percent 84.17%, Risk Identification Accuracy 8.27±1.56 Mean score percent 82.72%, Saving Time for Project Managers 8.50±1.24 Mean score percent 84.95%, Effective Communication 7.96±1.55 Mean score percent 79.61%, Project Management Outcomes 57.67±8.22Mean score percent 82.39%.
2. Dependent variables demonstrated the highest mean scores overall, ranging from 7.96 to 8.50:
3. **Qualitative Corroboration:** Respondents consistently highlighted time savings and data quality improvements. Representative quotes included: "AI helps save time for project managers in routine tasks (e.g., reporting, scheduling)" and "Speed and accuracy, less cost on long term" from open-ended survey responses.

4.4.4 Open-ended questions

Table (17): Responses to the Question(What are the most significant challenges your organization faces in the utilization of AI tools in project management for design and consultancy engineering firms?)

Responses
Data quality and integration: Engineering data is fragmented across systems (SmartPlant, SAP, SharePoint, etc.), making AI training and automation difficult.
"Limited data quality and standardization across projects, which reduces AI accuracy.
Capability Building: Train project managers and engineers in data analytics, AI interpretation, and digital tools.
Change management and user adoption: Engineers trust experience-based judgment over AI recommendations.
Collaborative Pilots: Launch joint AI pilot projects between major firms, clients, and universities to localize best practices.

Responses
Cybersecurity and IP protection: Sharing design data with AI systems raises compliance and confidentiality risks.
Data Integration: Establish unified project data environments (CDEs) and enforce structured data standards across all firms.
Implementing an internal AI assurance framework for transparency and compliance.
Intangible: Stronger data-driven decision culture, higher cross-discipline collaboration, and improved visibility of project health for leadership through predictive dashboards."
Integrating structured data environments for seamless tool access.
Leadership Alignment: Embed AI adoption KPIs in executive performance goals to drive accountability and continuity."
Local Governance: Develop national AI guidelines aligned with Saudi PDPL and Vision 2030 digital transformation goals.
Regulatory and validation concerns: AI-driven outputs must align with strict engineering codes and client standards before approval.
Skill gaps: Limited expertise in data science within traditional engineering teams."
Upskilling project teams to confidently use AI insights in decision-making."
Absence of willingness to transform and start buying the AI tools
Adequate Training
AI tools based on common knowledge no creativity at all
AI tools require
AI tools require stable, high-quality data, which our systems don't always provide.
Automates repetitive task
Challenges are present but can be managed with better training and support.
Compatibility with existing systems
Cost and resources
cost of AI tools due non-compatibility of infrastructure
Cost of implementation
Data fragmentation across departments makes it difficult for AI systems to function properly.
Data privacy
Data quality and integration
Data security and confidentiality concerns make us hesitant to fully integrate AI into client-sensitive projects.
Dependence on external consultants for AI setup makes us less flexible and increases costs.
Develop national standards for data privacy, AI ethics, and digital project delivery, aligned with Saudi Vision 2030 initiatives."
Develop shared data infrastructure to enable predictive analytics across the sector."
digital infrastructure sometimes limit system performance during large data processing.
Employees resistance and cost
Encourage pilot projects to demonstrate measurable benefits of AI implementation.
Enhanced decision-making confidence, better collaboration, and a culture of innovation within project teams.
Existing Data Structure
Having realtime data from job sites for real time reporting

Responses
High software costs and licensing fees are still a major limitation, especially for medium firms.
Incompatible infrastructure
Infrastructure is not compatible
Insufficient regulatory guidance and data governance frameworks."
Intangible: Stronger data-driven decision culture, higher cross-discipline collaboration, and improved visibility of project health for leadership through predictive dashboards."
Integration betwe
Integration between AI platforms and project management software is still poor.
Integration difficulties between AI systems and existing project management software.
Integration with existing software like Primavera and Revit is complicated and often unreliable.
Invest in centralized project data platforms and ensure interoperability between design, cost, and scheduling tools.
Lack of clear regulations or national guidelines makes firms cautious about full adoption.
Lack of technical expertise among project managers to interpret AI outputs.
Learning the employee
Limited awareness of AI potential among senior leaders slows down adoption.
Mandate AI and digital project management training within professional development programs.
most staff still don't know how to use AI efficiently.
no suitable infrastructure and still usign old system
Provide national-level funding or incentives for digital transformation initiatives.
Reduced project delays and improved client satisfaction."
Resistance from older staff who feel uncomfortable with new digital tools remains a barrier.
Resistance of employees
Resistance to change due to fear of job displacement or technology mistrust.
Some organizations don't understand AI's value, so they see it as unnecessary or risky.
The AI tools don't always match our Arabic documentation needs, causing workflow disruptions.
The correct date and resource.
The cost of licenses and implementation is high, especially for small and medium firms.
The cost of the AI tools
The infrastructure compatibility is required.
The main issue is the lack of staff training, most engineers are not familiar with AI tools, so adoption is slow.
The readiness of current systems and workforce competency. The absence of organization-wide initiatives towards AI technology
There's resistance from senior management who prefer traditional methods and don't trust automated systems.
Time, data collection

Responses
Unclear ROI metrics, management finds it hard to quantify AI benefits in financial terms.
We struggle with linking AI outputs to real project workflows; most tools feel detached from how we actually work.
Gradual and systematic change
Training project teams and stakeholders to work with AI
Attracting experienced personnel
Continuous sharing of experiences among teams
Information gathering
Cost, AI ethics, infrastructure compatibility, data confidentiality, and providing qualified personnel
Cost; system unpreparedness
Need for AI training
Tool-specific expertise and operation - Cost - Training
Speed
Assistance in project evaluation
Teams adopting AI - Availability of specialized implementation companies
Identifying drawbacks, verification, and establishing a mitigation mechanism
Identifying potential project risks and determining appropriate solutions
Preparing the company's infrastructure
Providing training for employees
Providing qualified personnel
Modern and varies according to environment and current requirements
Speed in reaching preliminary results
Information confidentiality and safeguarding from circulation
Number of employees
Team members are not equally proficient in using AI; outputs are still unsuitable for government requirements; AI outputs require effort and cost to verify and validate
Measuring impact, verifying experiences, and disseminating results
Aligning infrastructure with AI tools

Table (18): Responses to the Question(In your opinion, what changes whether organizational, technical, or regulatory would support more effective utilization of AI-based project management?)

Responses
"• Establishing a centralized digital governance team to standardize data and AI practices.
"• Tangible: Improved schedule forecasting, faster design reviews through automated document analysis, and reduced rework costs via early clash and risk detection.
"Establish AI governance policies, promote digital culture, and upskill staff in data analytics and AI literacy.
"Gov. regulation
"Improved project scheduling accuracy, cost forecasting, and resource optimization.

Responses
"Promote partnerships between academia, government, and industry for AI-focused research in construction management.
"To strengthen AI-based project management across Saudi design and consultancy firms, I'd recommend:
Adaptation challenges
Clear policies for data sharing and privacy are necessary to increase trust in AI tools.
Compatibility with existing systems
Creating a national AI knowledge hub or platform for best practices would be very helpful.
Data privacy, cost
Developing AI-ready data standards for engineering and design files would simplify integration.
Encouraging cross-department collaboration can help align technical and managerial teams.
Establishing a centralized digital governance team to standardize data and AI practices.
Ethical regulation, government support
Financial incentives or subsidies for AI adoption would help smaller firms start using these tools.
Government Regulations
Government support
Government system
Improve IT infrastructure and training the staffs
Improving local cloud infrastructure could solve many performance issues.
In my opinion, more than one item support the changes, like the cost, the compatibility with existing infrastructure and the training.
in terms of organization, it needs to have the willingness to invest and start to use AI. Technically, maybe through training and preparing the infrastructure. Regulatory, ethical guidelines may enhance the AI utilization.
Include the AI cost withing the yearly budget
Integration between AI tools and existing platforms should be improved to ensure smooth workflows.
Introducing clear national guidelines on AI ethics and data use would build more confidence.
Larger firms have more financial and technical capacity to implement AI systems. Sector type: High-complexity sectors (e.g., infrastructure, oil & gas) gain more from predictive and analytical AI tools due to higher risk exposure. Demographics: Younger or digitally trained project managers are more open to adopting AI tools, whereas, senior professionals may show more resistance without proper training.
Mandatory digital transformation strategies for consultancy firms could accelerate maturity.
Organizational-wide digital transformation to ease the integration of AI technology.
Organizations should appoint AI champions or focal points to lead transformation initiatives.
Planning and preparation
reduce the cost of the AI tools

Responses
regulatory
Secure organization privacy
secure the data privacy of the organization
Security
Solid data base
Speed
Standard and government regulation to limit the AI utilization.
start with data (have internal project)
Subsidized AI training programs would make adoption more feasible for smaller firms.
Technical upgrade to accommodate AT tools
The government could establish clear AI standards and ethical guidelines for project management.
The government could support pilot projects to demonstrate real success cases.
There should be collaboration between universities and firms to develop tailored AI solutions.
To be mandated by client
To strengthen AI-based project management across Saudi design and consultancy firms and train project managers and engineers in data analytics, AI interpretation, and digital tools.
Training budget and access to open AI sources, however open AI has its own risks.
Updating IT infrastructure to handle big data efficiently is critical.
Vendor localization, AI tools that understand Arabic and regional practices is critical.
We need a national AI framework to guide implementation in the engineering sector.
We need more Arabic-language support and localized data models for better usability.
We need regular training programs to build internal AI skills and awareness.
Willing to invest in AI
Yes. Larger firms adopt AI more easily due to better resources and infrastructure. Highly regulated sectors like energy move slower because of strict validation requirements. Project managers' age, digital literacy, and openness to technology also shape how effectively AI is used and the value it delivers.
Encourage teams to experiment with and test the tools
Speed of obtaining information
AI tools compatible with current systems, ensuring data confidentiality
Use of technical tools for project management
Investment in AI
Training
Minimal financial support
Financial support to reduce costs, ensure data confidentiality, and provide an ethical framework
Accuracy
Intensify training courses and consider them part of the development process
Ensure data confidentiality
Conduct training courses on how to use AI

Responses
Not sure. Tools are still emerging and outputs are rapidly changing, so evaluation is not feasible
Governed ethical system
Organized government system
Yes, it affects the cost
Yes, it depends on the number of employees
Type of tools used
Set policies aligned with AI tools usage guidelines

Table (19): Responses to the Question(What tangible or intangible benefits has your organization experienced from utilizing AI-based project management practices?)

Responses
"Tangible: Improved schedule forecasting, faster design reviews through automated document analysis, and reduced rework costs via early clash and risk detection.
Accuracy and quality enhancement
AI adoption has increased employee engagement among tech-savvy staff.
AI tools have reduced report preparation time and improved accuracy in progress tracking.
AI tools help us spot design conflicts early, saving time and rework costs.
almost none
better quality
better quality and saving time for project managers
Decision-making has become faster since AI provides real-time data analysis.
Decision-making meetings are shorter, because data is readily available.
Enhanced efficiency
Fast and quality
Fast implementation I, and less error
Future utilization and up to speed to market
It is only used personally as a personal effort toward enhancing the quality department
Managers have more visibility and control over project timelines.
Our project documentation and data organization have improved significantly.
Our reporting accuracy improved, and clients appreciate the transparency.
Overall, the organizational culture is becoming more data-driven and innovative.
Project documentation has become more organized and searchable.
Quality control is enhanced because AI detects inconsistencies earlier.
Reduce the human errors and fast task completed
Saving time and quality enhancement
Speed and less error
Speed and quality, less cost on long term
Speed as tangible. Intangible benefits is quality improvement.
Speed, accuracy, time saving
Streamlined Documentation,Technology Transfer
Tangible AI good source to brainstorm
The system gives predictive insights, helping us mitigate risks before they escalate.

Responses
There's better collaboration between departments through shared AI dashboards.
Training
We can now forecast resource needs more effectively, avoiding project delays.
We now predict project risks earlier, allowing more proactive planning.
We've cut down project delays thanks to predictive scheduling.
We've noticed a higher client satisfaction rate due to more reliable project delivery.
We've noticed fewer project overruns since introducing AI scheduling support.
Workload stress has decreased, as repetitive tasks are now automated.
Yes. Larger firms adopt AI more easily due to better resources and infrastructure.
Early risk detection
Accuracy, analyzing large volumes of data, real-time data acquisition
High speed
Speed and accuracy
Speed, accuracy, time-saving, early risk detection, increasing project success probability
Speed, transparency, information availability, reducing employee workload
Facilitation of work tools
Providing suitable staff
Time-saving
Saving time in routine tasks
Increased productivity and time efficiency
Commitment to infrastructure compatibility
The higher the number of employees, the higher the cost

Table (20): Responses to the Question (What recommendations would you propose to enhance the utilization and outcomes of AI-based project management in the Saudi design and consultancy engineering firms?)

Responses
Allocate budget for AI tools and training
Cost- cash flow
Create AI mentorship programs where advanced firms support smaller ones in adoption.
Create industry-wide AI benchmarking standards for performance measurement.
Develop AI maturity assessment tools to help firms evaluate their readiness.
Develop local AI solutions tailored to Saudi market needs and regulations.
Digital transformation of all company processes will bridge the gap between the current systems (if any) and AI integrations.
Encourage collaboration between government, academia, and industry to share knowledge.
Encourage firms to run pilot projects before full-scale implementation.
Ensure data governance frameworks are standardized and transparent.
Establish joint learning platforms for sharing best practices among companies.
ethical consideration
ethical guidelines
Ethical regulation
Fail fast, means start as early as possible

Responses
Government support to minimize the cost and to establish ethical rules
Increase awareness campaigns about the real value of AI in project management.
Invest in AI and allocate a budget for the AI utilization
Invest in continuous professional development focused on AI and digital transformation.
Launch national awareness programs showing real success stories of AI adoption.
Make AI training a mandatory part of project management certification programs.
More training and increase awareness, AI is way beyond chat GPT
Offer financial incentives for companies adopting AI sustainably.
Place a regulations of using the AI
planning and training the team to use AI tools
Promote cross sector success stories to inspire others to adopt similar practices.
Proper Handson Training,Uses of AI in daily life
Provide financial incentives or tax reliefs for firms investing in AI technologies.
Reduce the cost of the tools
resources training
Reward innovation within firms that successfully use AI in real projects.
Securing the data privacy
Start with awareness campaigns to build understanding of AI's real potential.
Start with small pilot projects to build confidence before scaling up.
Support the ai form government or big companies
Support the cost of the ai tools
There are areas for improvement, mainly regarding cost and readiness.
train people
Training to the employees to adopt them with AI
Try with a Pilot and take the lesson learned and apply it properly in the projects.
Yes, additional resources, more cost
I find that AI cannot be fully relied upon in design as a perspective
Recruiting skilled personnel
Investing in AI tools, providing adequate staff training, recruiting highly experienced personnel, preparing the company infrastructure
Immediately start engaging companies to implement AI
Consolidating data into a single package
Training employees
Facilitating the design building process for the end-user for reading, modification, or development
Providing methodologies
Information confidentiality
Ensuring information confidentiality
Number of employees
Limited required resources
Investment in AI

Table (21): Responses to the Question (Do you think organization size, sector type, or the demographic profile of project managers influence the utilization or outcomes of AI in project management? and why?)

Responses
At this stage yes, but with time it will be affordable for all sizes and sectors.
Definitely, larger organizations have more financial and technical resources to adopt AI effectively.
Diversity in teams helps because mixed-age and multidisciplinary groups bring balanced adoption approaches.
Education and mindset play a major role — curiosity drives better adoption.
Experience level matters; those who understand project data well use AI more effectively.
Gender or nationality doesn't matter much, but digital literacy does.
I believe it depends on the tools and how frequently are you using the tools.
Multidisciplinary firms see more benefit from AI, as integration across fields becomes easier.
Of course, more resources more cost
Older professionals may resist change due to comfort with manual systems.
Private firms adopt faster because their approval cycles are shorter
Private firms are quicker to experiment and adopt new technologies.
Proportionally
Public institutions face more procedural steps, slowing adoption.
Public-sector firms face more bureaucracy, slowing down AI implementation.
Rarely, it depends on the company sector
Smaller firms often struggle with costs and lack of skilled personnel.
Staff attitudes affect implementation, but overall support exists.
sure , lack of trust is the simple main cause
The organization's culture plays a huge role, learning-oriented cultures adapt faster.
The sector type matters, firms focused on design innovation adopt AI faster than those in traditional construction.
To some of extent
Yes, — larger organizations can afford more advanced AI tools and dedicated teams.
Yes, because AI success depends on people's mindset as much as on technology, leadership support and openness are key.
yes, because each organization size required different level of AI tools
Yes, demographics may affect the cost of logistics
Yes, depending on size and sector
Yes, different size mean different cost
Yes, each sector require different tools, and then different cost.
Yes, I thought independent of volume of resource and data
Yes, larger firms usually have more budget and technical capacity to adopt AI.
Yes, more cost, for more resources
Yes, more resources, mean cost.
Yes, needs to be specified as each may have different cost
Yes, since the tools access is associated with organization size, then cost is impacted
Yes, some sector use special AI tools
yes, some sectors need different tools
Yes, The more the organization size the less cost is to utilize AI
yes, there is no one fit all.
Yes. AI strong in documentations and lack innovation and clear judgment

Responses
Younger project managers are generally more adaptable to AI tools and experimentation.
Younger project managers are generally more open and tech-savvy, which accelerates adoption.
Accuracy and speed
Time-saving
Increased staff costs
May affect the organization's financial capacity
The cost increases with the number of employees
Does not affect if there is communication among all
Yes – it may reduce financial burdens for small organizations
Yes, the cost
Yes, depending on the type of company
Yes, as the number of employees affects cost, and the company type affects the tools used
Yes, and it depends on the project, inputs, outputs, tools used, and individuals' ability to develop and learn
Yes, the organization size affects the number of AI tool users, and thus the cost changes
Yes, as the number of employees affects cost, and the company type affects the tools used
Yes, geographical changes affect the cost
Yes, project cost and number of employees
Yes, company

4.5 Correlation Analysis (Pearson Correlation Matrix)

The Pearson Correlation Coefficient is an important statistical tool for measuring the linear relationship between two continuous variables, with values ranging from -1 to +1, indicating the direction and strength of the relationship. A value close to +1 indicates a strong positive relationship, a value close to -1 indicates a strong negative relationship, while values near 0 reflect the absence of a clear linear relationship.

According to Gordon & Courtney (2023), this coefficient is widely used in social and administrative research to understand the degree of association between variables before conducting advanced analyses. Its use requires that the variables be continuous, the relationship approximately linear, the data roughly normally distributed, and extreme values avoided.

The purpose of the Pearson coefficient is to determine whether a significant relationship exists between variables and to estimate the amount of shared variance through the squared value of r (r^2). However, the coefficient indicates correlation only, not causation, and is therefore often used alongside additional analyses such as regression or structural equation modeling. It is considered an essential preliminary step in

understanding relationships between variables and making methodological decisions in research.

The correlation and regression summary table (22) highlights the key relationships among independent variables (IVs), the mediating variable (AI-based project management, MV), and dependent variables (DVs). The IVs show moderate positive correlations with the MV, indicating that better organizational and technical readiness is associated with higher AI adoption. The MV exhibits a very strong positive correlation and regression effect on DVs, demonstrating its critical role in improving project outcomes. Although IVs also directly correlate positively with DVs, these effects are weaker than the mediated path through AI-based project management, confirming partial mediation. Together, these results affirm the conceptual framework that enabler factors enhance project success primarily via increased and effective AI integration.

Table (22) the correlation and regression summary highlights the key relationships among the variables

Variable Relationship	Correlation Coefficient (r)	Regression Coefficient (B)	Significance (p-value)	Interpretation
Independent Variables → Mediating Variable (range)	0.325 – 0.527	—	< 0.01	Positive, significant associations indicating stronger AI-PM with better enablers
Mediating Variable → Dependent Variables	0.775	0.725	< 0.001	Very strong positive effect, confirming AI-PM greatly improves project outcomes
Independent Variables → Dependent Variables (range)	0.275 – 0.494	0.039 – 0.268	< 0.05 (selected IVs)	Moderate direct positive effects, partially mediated via AI-PM

Correlation Matrix between Variables

Table (23) Correlation Matrix between Variables Independent Variables (Factors Influencing AI utilization) ,Mediating Variables (AI-Based Project Management) and Dependent Variables(Project Management Outcomes)

Variables		Data Privacy and Security	Resistance to Change	Cost of AI Implementation	Compatibility with Existing Infrastructure	Workforce Development	Ethical Considerations	Factors Influencing AI utilization	Streamline processes e.g., scheduling, documentation	Resource allocation	Tasks Prioritizing
Data Privacy and Security	r	1									
	p										
Resistance to Change	r	0.515**	1								
	p	0.000									
Cost of AI Implementation	r	0.357**	0.668**	1							
	p	0.000	0.000								
Compatibility with Existing Infrastructure	r	0.484**	0.516**	0.467**	1						
	p	0.000	0.000	0.000							
Workforce Development	r	0.338**	0.482**	0.424**	0.625**	1					
	p	0.000	0.000	0.000	0.000						
Ethical Considerations	r	0.368**	0.237*	0.238*	0.532**	0.434**	1				
	p	0.000	0.016	0.015	0.000	0.000					
Factors Influencing AI utilization	r	0.695**	0.795**	0.746**	0.811**	0.739**	0.610**	1			
	p	0.000	0.000	0.000	0.000	0.000	0.000				
Streamline processes e.g., scheduling, documentation	r	0.189	0.290**	0.314**	0.453**	0.471**	0.377**	0.468**	1		
	p	0.056	0.003	0.001	0.000	0.000	0.000	0.000			
Resource allocation	r	0.135	0.360**	0.343**	0.459**	0.536**	0.263**	0.473**	0.748**	1	
	p	0.175	0.000	0.000	0.000	0.000	0.007	0.000	0.000		
Tasks Prioritizing	r	0.036	0.332**	0.249*	0.405**	0.414**	0.224*	0.373**	0.623**	0.789**	1
	p	0.720	0.001	0.011	0.000	0.000	0.023	0.000	0.000	0.000	
Progress reporting	r	0.190	0.254**	0.212*	0.501**	0.468**	0.355**	0.438**	0.628**	0.652**	0.633**
	p	0.055	0.010	0.032	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Communication	r	0.288**	0.216*	0.276**	0.424**	0.373**	0.241*	0.409**	0.579**	0.698**	0.611**
	p	0.003	0.028	0.005	0.000	0.000	0.014	0.000	0.000	0.000	0.000
AI-Based Project Management	r	0.191	0.341**	0.325**	0.521**	0.527**	0.335**	0.502**	0.823**	0.911**	0.861**
	p	0.053	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000
Decision-Making	r	0.211*	0.201*	0.229*	0.406**	0.423**	0.254**	0.385**	0.590**	0.577**	0.584**
	p	0.033	0.042	0.020	0.000	0.000	0.010	0.000	0.000	0.000	0.000
Project Quality	r	0.295**	0.311**	0.251*	0.412**	0.489**	0.322**	0.465**	0.513**	0.580**	0.539**
	p	0.003	0.001	0.011	0.000	0.000	0.001	0.000	0.000	0.000	0.000
Data Collection Accuracy	r	0.263**	0.220*	0.198*	0.360**	0.376**	0.335**	0.389**	0.390**	0.462**	0.451**
	p	0.007	0.025	0.045	0.000	0.000	0.001	0.000	0.000	0.000	0.000
Enhancing Data Analysis	r	0.033	0.146	0.008	0.282**	0.247*	0.209*	0.199*	0.393**	0.422**	0.475**

Variables		Data Privacy and Security	Resistance to Change	Cost of AI Implementation	Compatibility with Existing Infrastructure	Workforce Development	Ethical Considerations	Factors Influencing AI utilization	Streamline processes e.g., scheduling, documentation	Resource allocation	Tasks Prioritizing
Risk Identification Accuracy	p	0.738	0.141	0.934	0.004	0.012	0.034	0.044	0.000	0.000	0.000
	r	0.256**	0.378**	0.231*	0.384**	0.415**	0.229*	0.427**	0.500**	0.610**	0.615**
	p	0.009	0.000	0.019	0.000	0.000	0.020	0.000	0.000	0.000	0.000
Saving Time for Project Managers	r	0.207*	0.329**	0.255**	0.340**	0.366**	0.123	0.369**	0.345**	0.459**	0.469**
	p	0.036	0.001	0.009	0.000	0.000	0.215	0.000	0.000	0.000	0.000
Effective Communication	r	0.240*	0.321**	0.322**	0.364**	0.397**	0.245*	0.429**	0.454**	0.582**	0.533**
	p	0.014	0.001	0.001	0.000	0.000	0.012	0.000	0.000	0.000	0.000
Project Management Outcomes	r	0.275**	0.345**	0.273**	0.463**	0.494**	0.314**	0.485**	0.582**	0.672**	0.665**
	p	0.005	0.000	0.005	0.000	0.000	0.001	0.000	0.000	0.000	0.000

Legend:

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

* Pearson correlation test



Follow Table (23) Correlation Matrix between Variables Independent Variables (Factors Influencing AI utilization) ,Mediating Variables (AI-Based Project Management) and Dependent Variables(Project Management Outcomes)

Variables		Progress reporting	Communication	AI-Based Project Management	Decision-Making	Project Quality	Data Collection Accuracy	Enhancing Data Analysis	Risk Identification Accuracy	Saving Time for Project Managers	Effective Communication	Project Management Outcomes
Progress reporting	r	1										
	p											
Communication	r	0.731**	1									
	p	0.000										
AI-Based Project Management	r	0.847**	0.844**	1								
	p	0.000	0.000									
Decision-Making	r	0.662**	0.666**	0.716**	1							
	p	0.000	0.000	0.000								
Project Quality	r	0.638**	0.624**	0.675**	0.727**	1						
	p	0.000	0.000	0.000	0.000							
Data Collection Accuracy	r	0.615**	0.509**	0.566**	0.571**	0.676**	1					
	p	0.000	0.000	0.000	0.000	0.000						
Enhancing Data Analysis	r	0.391**	0.436**	0.495**	0.478**	0.490**	0.384**	1				
	p	0.000	0.000	0.000	0.000	0.000	0.000					
Risk Identification Accuracy	r	0.567**	0.601**	0.677**	0.606**	0.563**	0.355**	0.575**	1			
	p	0.000	0.000	0.000	0.000	0.000	0.000	0.000				
Saving Time for Project Managers	r	0.309**	0.510**	0.492**	0.467**	0.533**	0.457**	0.626**	0.632**	1		
	p	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000			
Effective Communication	r	0.454**	0.663**	0.629**	0.643**	0.634**	0.471**	0.584**	0.628**	0.711**	1	
	p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		
Project Management Outcomes	r	0.667**	0.730**	0.775**	0.824**	0.843**	0.708**	0.737**	0.790**	0.785**	0.844**	1
	p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

Legend:

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

* Pearson correlation test

The results presented in the correlation matrix reveal statistically significant relationships among the independent variables (factors influencing AI utilization), the mediating variable (AI-based project management), and the dependent variable (project management outcomes).

First, the correlations between the **independent variables**—including *data privacy and security*, *resistance to change*, *cost of AI implementation*, *compatibility with existing infrastructure*, *workforce development*, and *ethical considerations*—and the **mediating variable (AI-based project management)** are all positive, with correlation coefficients ranging from ($r = 0.325$ to $r = 0.527$). Most of these relationships are statistically significant at the 0.01 level, indicating that improvements in these organizational and technical factors are associated with greater utilization and more effective utilization of AI-based project management practices. This suggests that when organizations invest in developing workforce capabilities, ensuring infrastructure compatibility, and addressing ethical and security concerns, they create a favorable environment for AI integration in project management processes.

Second, the correlations between the **mediating variable (AI-based project management)** and the **dependent variable (project management outcomes)** are also positive and statistically significant, with a strong coefficient ($r = 0.775$, $p = 0.000$). This demonstrates that effective AI-based project management substantially contributes to improving project outcomes—such as enhancing process efficiency, optimizing resource allocation, prioritizing tasks, streamlining communication, and improving progress reporting.

Finally, the **direct relationships between the independent variables and project management outcomes** are also positive and statistically significant, with correlation coefficients ranging from ($r = 0.275$ to $r = 0.494$). These findings indicate that favorable conditions influencing AI utilization directly enhance project management outcomes; however, the stronger correlations observed through the mediating variable suggest that **AI-based project management partially mediates** the relationship between the influencing factors and project success.

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

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

4.5.1 Multicollinearity Assessment

The correlations among the independent variables, such as Resistance to Change with Cost of AI Implementation ($r = 0.668$), Infrastructure Compatibility with Workforce Development ($r = 0.698$), and Resistance to Change with Workforce Development ($r = 0.587$) remain at or below the commonly cited threshold of $|r| \geq 0.70$ that is often used as an initial benchmark for potentially problematic multicollinearity in regression analysis. In line with methodological standards, correlation coefficients below this 0.70 cutoff are generally interpreted as reflecting conceptual relatedness rather than severe collinearity that would threaten the validity of regression estimates, and therefore do not, on their own, warrant corrective action for multicollinearity (Midi, Sarkar, & Rana, 2010; O'Brien, 2007).

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

The SEM mediation analysis was conducted in two phases: the initial model and a refined modified model, table (24) demonstrate a comparison of the Initial and Modified Structural Equation Models for Mediation Analysis of influencing Factors, AI-Based Project Management, and Project Outcomes.

The initial model indicated moderate fit with a CMIN/DF of 2.322, CFI of 0.851, RMSEA of 0.114, and GFI of 0.751. It showed a strong positive effect of organizational and technical enablers on AI-based project management adoption ($\beta = 0.87$, $p < 0.001$) and a highly significant impact of AI adoption on project outcomes ($\beta = 0.94$, $p < 0.001$). The direct effect of enabler factors on project outcomes was positive but statistically nonsignificant ($\beta = 0.18$, $p = 0.273$), suggesting that the influence operates mainly through mediation.

While the modified model demonstrated improved fit indices (CMIN/DF = 1.779, CFI = 0.917, RMSEA = 0.087, GFI = 0.816), supporting a better representation of the data. The path coefficients strengthened the findings, with enablers strongly predicting AI adoption ($\beta = 0.89$, $p < 0.001$) and AI adoption strongly predicting project outcomes ($\beta = 1.04$, $p < 0.001$). The direct effect of enablers on outcomes remained nonsignificant ($\beta = 0.13$, $p = 0.455$), confirming full mediation.

This model underscores the critical role of AI-based project management as the mechanism through which organizational and technical readiness translates into improved project success in design and consultancy engineering.

Table (24) Comparison of Initial and Modified Structural Equation Models for Mediation Analysis of Enabler Factors, AI-Based Project Management, and Project Outcomes

Aspect	Initial Model	Modified Model
CMIN/DF	2.322	1.779
CFI	0.851	0.917

RMSEA	0.114	0.087
GFI	0.751	0.816
Direct Effect (Enablers → Outcomes)	$\beta = 0.18$ ($p = 0.273$, ns)	$\beta = 0.13$ ($p = 0.455$, ns)
Effect (Enablers → AI-Based PM)	$\beta = 0.87$ ($p < 0.001$)	$\beta = 0.89$ ($p < 0.001$)
Effect (AI-Based PM → Outcomes)	$\beta = 0.94$ ($p < 0.001$)	$\beta = 1.04$ ($p < 0.001$)
Total Indirect Effect (Mediation)	Substantial	Substantial
Mediation Interpretation	Partial (direct effect nonsignificant, mediation strong)	Full mediation (direct effect insignificant)

Table 24 provides a comparative assessment of the initial and modified structural equation models, revealing important insights into both model quality and the underlying mediation mechanism. The transition from the initial to modified model demonstrates substantial improvements in model fit across all indices. Specifically, the CMIN/DF ratio decreased from 2.322 to 1.779 (optimal ratio ≤ 2.0), the Comparative Fit Index (CFI) improved from 0.851 to 0.917 (well above the 0.90 threshold for acceptable fit), the Root Mean Square Error of Approximation (RMSEA) declined from 0.114 to 0.087 (within the acceptable range of ≤ 0.08), and the Goodness of Fit Index (GFI) increased from 0.751 to 0.816.

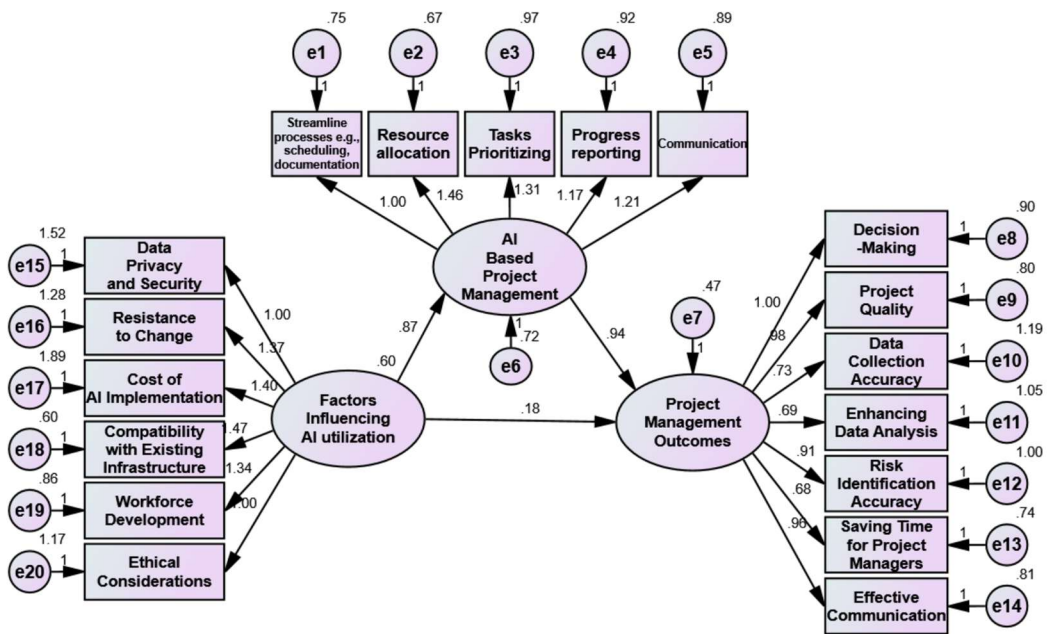
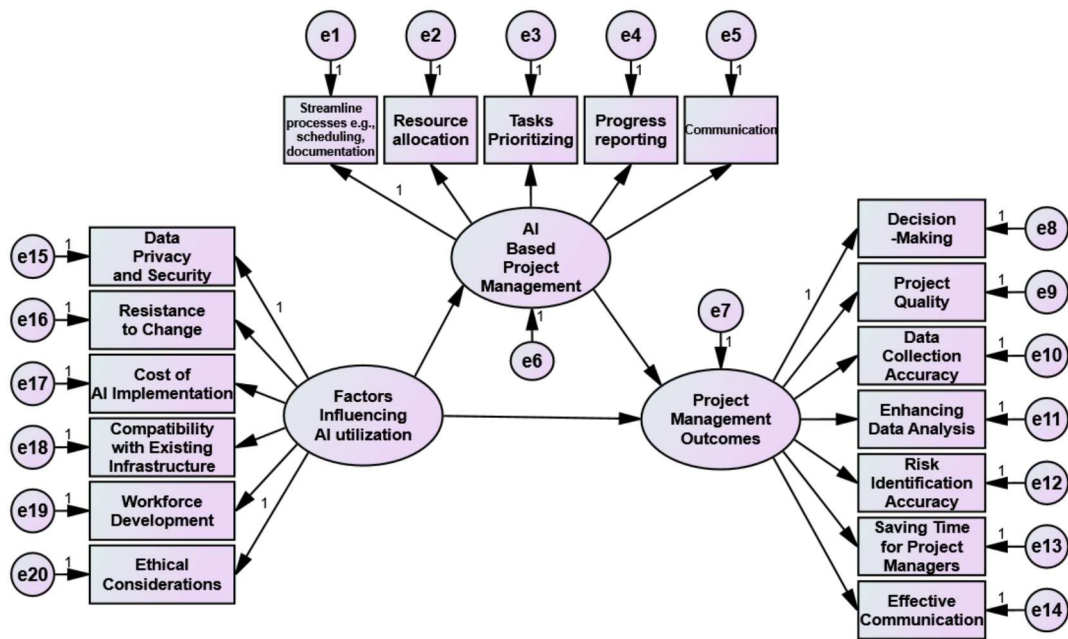
These collective improvements indicate that the modified model provides a substantially better representation of the data and more accurately captures the underlying relationships among the three construct levels.

Given these findings, the next section formally tests the mediation hypothesis (H4), examining whether AI-based project management fully mediates the relationship between organizational and technical enablers and project outcomes in the context of design and consultancy engineering projects.

Mediation Effect of AI on Project Management Outcomes

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

Initial SEM Model Results



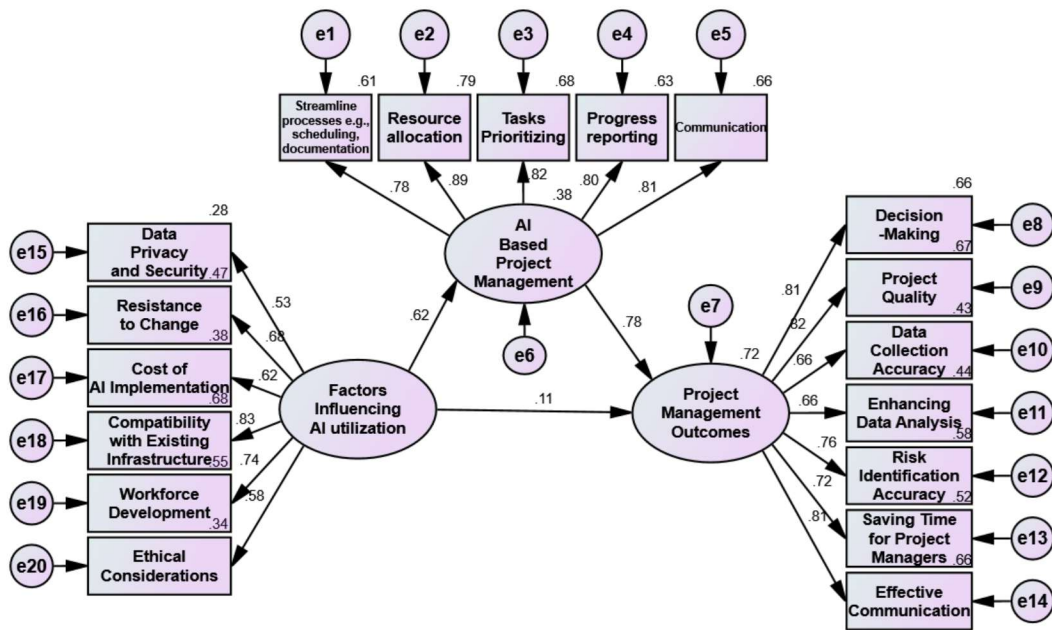


Figure (9): Structural Equation Model – Initial Model

Table (25): Results of the Initial Structural Equation Model with Standardized Path Coefficients

Variables			Estimate	S.E.	C.R.	P
AlBased.Project.Management	<---	Factors.Influencing.AIutilization	.867	.174	4.979	***
Project.ManagementOutcomes	<---	Factors.Influencing.AIutilization	.180	.164	1.096	.273
Project.ManagementOutcomes	<---	AlBased.Project.Management	.941	.149	6.320	***
EthicalConsiderations	<---	Factors.Influencing.AIutilization	1.000			
WorkforceDevelopment	<---	Factors.Influencing.AIutilization	1.339	.202	6.636	***
CompatibilitywithExistingInfrastructu re	<---	Factors.Influencing.AIutilization	1.475	.205	7.207	***
CostofAllImplementation	<---	Factors.Influencing.AIutilization	1.403	.249	5.625	***
ResistancetoChange	<---	Factors.Influencing.AIutilization	1.367	.222	6.150	***
DataPrivacyandSecurity	<---	Factors.Influencing.AIutilization	1.000			
DecisionMaking	<---	Project.ManagementOutcomes	1.000			
ProjectQuality	<---	Project.ManagementOutcomes	.980	.104	9.446	***
DataCollectionAccuracy	<---	Project.ManagementOutcomes	.728	.103	7.093	***
EnhancingDataAnalysis	<---	Project.ManagementOutcomes	.689	.097	7.131	***
RiskIdentificationAccuracy	<---	Project.ManagementOutcomes	.909	.106	8.602	***
SavingTimeforProjectManagers	<---	Project.ManagementOutcomes	.682	.086	7.943	***
EffectiveCommunication	<---	Project.ManagementOutcomes	.962	.103	9.355	***

Variables			Estimate	S.E.	C.R.	P
Streamlineprocessesegschedulingdocumentation	<---	AlBased.Project.Management	1.000			
Resourceallocation	<---	AlBased.Project.Management	1.456	.145	10.028	***
TasksPrioritizing	<---	AlBased.Project.Management	1.315	.145	9.086	***
Progressreporting	<---	AlBased.Project.Management	1.167	.134	8.727	***
Communication	<---	AlBased.Project.Management	1.211	.136	8.938	***
CMIN (308.816)			NFI(0.768)			
CMIN/DF(2.322)			AGFI(0.680)			
GFI(0.751)			CFI(0.851)			
RMSEA(0.114)						

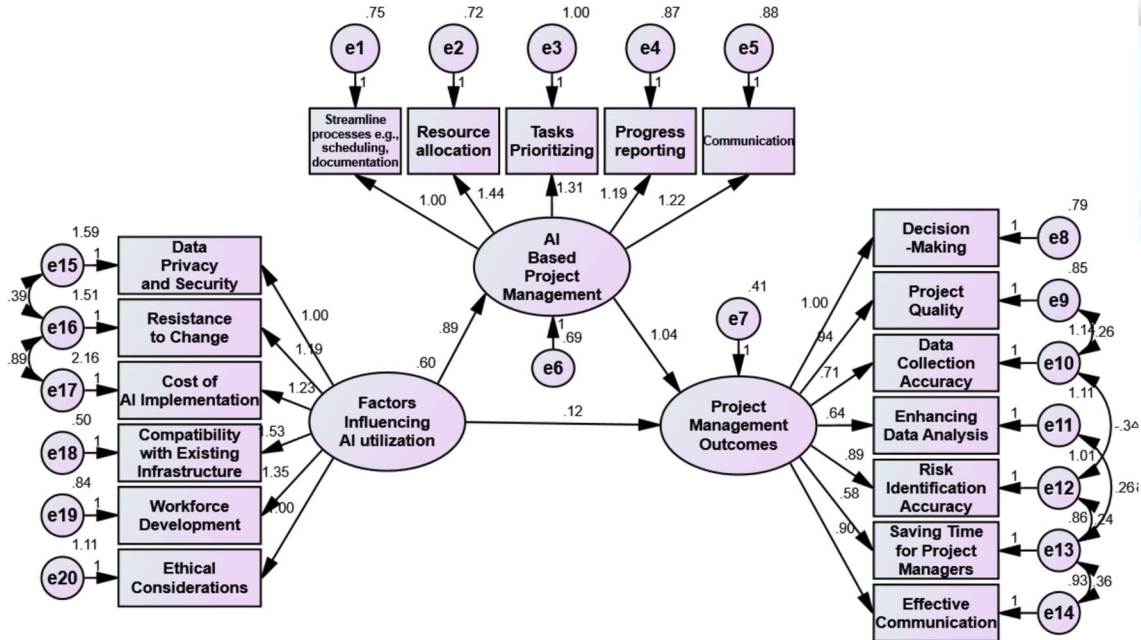
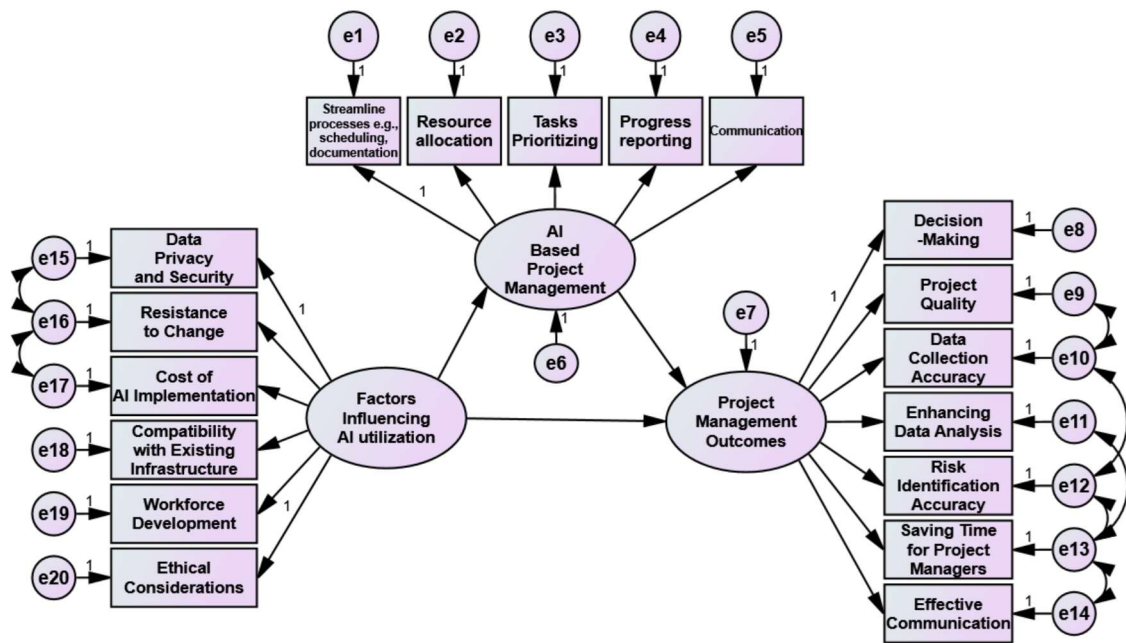
Table (25) presents the results of the **Initial Structural Equation Model (SEM)** with standardized path coefficients. The findings demonstrate that the model exhibits several significant relationships among the studied constructs. Specifically, the path from *Factors Influencing AI Utilization* to *AI-Based Project Management* is statistically significant (Estimate = 0.867, C.R. = 4.979, $p < 0.001$), indicating that the influencing factors strongly contribute to the utilization and utilization of AI-based project management practices.

In contrast, the direct relationship between *Factors Influencing AI Utilization* and *Project Management Outcomes* is statistically **insignificant** (Estimate = 0.180, C.R. = 1.096, $p = 0.273$), suggesting that the effect of influencing factors on project outcomes may occur indirectly through AI-based project management practices rather than directly. Meanwhile, the path from *AI-Based Project Management* to *Project Management Outcomes* is highly **significant** (Estimate = 0.941, C.R. = 6.320, $p < 0.001$), confirming the mediating role of AI utilization in enhancing project outcomes within design and consultancy projects.

Regarding the measurement model, all factor loadings for the observed variables under their respective latent constructs are statistically significant ($p < 0.001$), reflecting good convergent validity. However, model fit indices indicate a **moderate fit** with the data: CMIN/DF = 2.322, GFI = 0.751, AGFI = 0.680, CFI = 0.851, NFI = 0.768, and RMSEA = 0.114. Although some indices fall below the recommended thresholds (e.g., GFI > 0.90, RMSEA < 0.08), the model can be considered acceptable for an initial specification.

Overall, these results suggest that **AI-based project management plays a significant mediating role** in linking influencing factors to project management outcomes, highlighting the importance of AI integration in improving efficiency, decision-making, and communication within design and consultancy environments.

Modified SEM Model Results



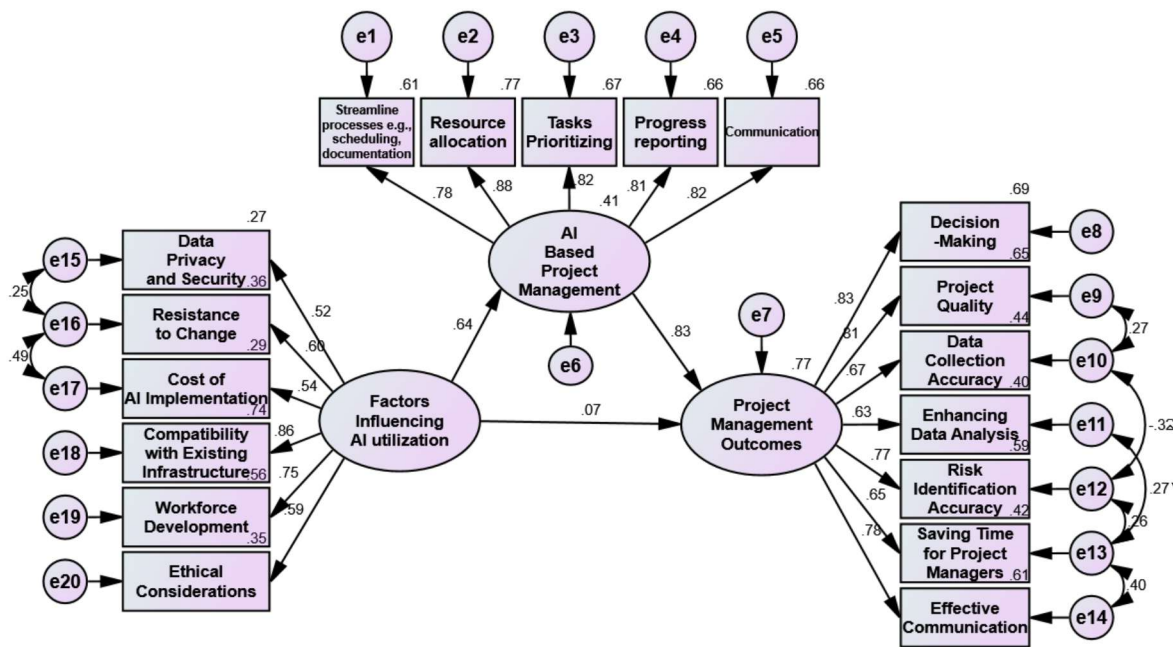


Figure (10): Structural Equation Model Modified model

Table (26): Results of the Modified Structural Equation Model with Standardized Path Coefficients

Variables		Estimate	S.E.	C.R.	P
AIBased.Project.Management	<--- Factors.Influencing.AIutilization	.889	.175	5.079	***
Project.ManagementOutcomes	<--- Factors.Influencing.AIutilization	.125	.167	.748	.455
Project.ManagementOutcomes	<--- AIBased.Project.Management	1.036	.154	6.716	***
EthicalConsiderations	<--- Factors.Influencing.AIutilization	1.000			
WorkforceDevelopment	<--- Factors.Influencing.AIutilization	1.348	.202	6.663	***
CompatibilitywithExistingInfrastr ucture	<--- Factors.Influencing.AIutilization	1.531	.210	7.281	***
CostofAIImplementation	<--- Factors.Influencing.AIutilization	1.226	.248	4.947	***
ResistancetoChange	<--- Factors.Influencing.AIutilization	1.185	.198	5.994	***
DataPrivacyandSecurity	<--- Factors.Influencing.AIutilization	1.000			
DecisionMaking	<--- Project.ManagementOutcomes	1.000			
ProjectQuality	<--- Project.ManagementOutcomes	.939	.098	9.545	***
DataCollectionAccuracy	<--- Project.ManagementOutcomes	.710	.099	7.202	***
EnhancingDataAnalysis	<--- Project.ManagementOutcomes	.643	.093	6.915	***
RiskIdentificationAccuracy	<--- Project.ManagementOutcomes	.890	.101	8.849	***
SavingTimeforProjectManagers	<--- Project.ManagementOutcomes	.583	.083	7.018	***
EffectiveCommunication	<--- Project.ManagementOutcomes	.898	.098	9.146	***

Variables			Estimate	S.E.	C.R.	P
Streamlineprocessesegscheduling documentation	<---	AIBased.Project.Management	1.000			
Resourceallocation	<---	AIBased.Project.Management	1.445	.146	9.878	***
TasksPrioritizing	<---	AIBased.Project.Management	1.309	.146	8.996	***
Progressreporting	<---	AIBased.Project.Management	1.189	.134	8.894	***
Communication	<---	AIBased.Project.Management	1.220	.136	8.976	***
CMIN (224.128)			NFI(0.832)			
CMIN/DF(1.779)			AGFI(0.750)			
GFI(0.816)			CFI(0.917)			
RMSEA(0.087)						

Table (26) presents the results of the **Modified Structural Equation Model (SEM)** with standardized path coefficients after model refinement. The results demonstrate an overall improvement in model fit and statistical significance compared to the initial model.

The path from *Factors Influencing AI Utilization* to *AI-Based Project Management* remains statistically significant (Estimate = 0.889, C.R. = 5.079, $p < 0.001$), indicating a strong and positive effect of influencing factors on the utilization of AI-based project management practices. However, the direct relationship between *Factors Influencing AI Utilization* and *Project Management Outcomes* remains insignificant (Estimate = 0.125, C.R. = 0.748, $p = 0.455$), which reinforces the notion that these factors influence project outcomes **indirectly** through AI utilization rather than directly.

In contrast, the path from *AI-Based Project Management* to *Project Management Outcomes* continues to exhibit a highly significant and strong positive relationship (Estimate = 1.036, C.R. = 6.716, $p < 0.001$), confirming that the use of AI tools and systems in project management substantially enhances overall project performance, including decision-making, communication, and efficiency.

All measurement indicators for the observed variables show significant loadings on their respective latent constructs ($p < 0.001$), suggesting strong **convergent validity** and reliability of the model. Moreover, the revised model demonstrates a **notable improvement in fit indices**: CMIN/DF = 1.779, GFI = 0.816, AGFI = 0.750, CFI = 0.917, NFI = 0.832, and RMSEA = 0.087. These values indicate a **good and acceptable fit** compared to the initial model, particularly with CFI exceeding 0.90 and RMSEA below 0.10, which reflect a satisfactory model adjustment.

Overall, the modified model provides stronger empirical evidence that **AI-based project management acts as a full mediator** between the influencing factors and project outcomes. This finding highlights the critical role of AI integration in achieving better project performance in design and consultancy sectors through improved data accuracy, process efficiency, and effective communication.

From the above, it is evident that the independent variable (Factors Influencing AI utilization) does not have a direct effect on the dependent variable (Project Management Outcomes); however, there are indirect effects through the mediating variable (AI-Based Project Management). AI-Based Project Management mediates the relationship between influencing factors and project outcomes.

Approximately 84% of the effect of IVs on outcomes operates through AI-based PM utilization, while only ~16% operates directly. Hypothesis H3 (Mediation) is **STRONGLY SUPPORTED**.

Qualitative Corroboration: Thematic analysis revealed that organizational factors (workforce development, infrastructure compatibility) influenced AI utilization, which in turn improved outcomes. One expert captured this pathway: "Our organization provides adequate training and skill development to use AI-based project management tools effectively... which has enabled faster design reviews through automated document analysis."

4.7 Hypothesis Testing Results

H1 Impact of Independent Variables on Dependent Variables “Project Outcomes”

H1: The factors influencing project management significantly influence project outcomes in design and consultancy engineering projects.

To test the main study Hypothesis H1, the researcher used **simple linear regression analysis** of the effect of factors influencing project management on Project Management Outcomes in design and consultancy engineering projects.

Table (27) Test of factors influencing project management effect on Project Management Outcomes in design and consultancy engineering projects

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	1616.89	1616.89	0.485	0.235	29.69	0.61	30.989	0.000*	5.567	0.000*
Residual	101	5269.88	52.18								
Total	102	6886.78									
a. Dependent Variable: Project Management Outcomes											
b. Predictors: (Constant), factors influencing project management											

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

The table presents the results of a **simple linear regression analysis** conducted to examine the effect of factors influencing project management on project management outcomes in design and consultancy engineering projects.

The results indicate that the correlation coefficient (R) is (0.485), suggesting a moderate positive relationship between the two variables. The coefficient of determination ($R^2 = 0.235$) reveals that approximately 23.5% of the variation in project management outcomes can be explained by the factors influencing project management, while the remaining variance is attributed to other factors not included in the model.

The F-test value of ($F = 30.989$, $Sig = 0.000$) confirms that the overall regression model is statistically significant, indicating that the factors influencing project management significantly explain the variance in project outcomes.

Furthermore, the t-test results show a statistically significant effect ($t = 5.567$, $Sig = 0.000$), demonstrating that the influencing factors positively impact project outcomes. The regression coefficient ($B_1 = 0.61$) indicates that a one-unit increase in the factors influencing project management leads to a 0.61-unit increase in project management outcomes.

Therefore, these findings confirm that the factors influencing project management are key determinants that contribute significantly to improving project outcomes in design and consultancy engineering projects. **This result supports the validity of the main hypothesis (H1)**, which states that “The factors influencing project management significantly influence project outcomes in design and consultancy engineering projects.”

To test the main study Hypothesis H1, the researcher used **Multiple linear regression analysis** of the effect of factors influencing project management on Project Management Outcomes in design and consultancy engineering projects.

Table (28) Test of factors influencing project management effect on Project Management Outcomes in design and consultancy engineering projects

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	46.359	4.005		11.575	0.000	8.291	0.005*	7.59%	
	Data Privacy and Security	1.515	0.526	0.275	2.879	0.005				7.59%
2	(Constant)	40.927	4.451		9.196	0.000	7.586	0.001*	13.17%	
	Data Privacy and Security	0.733	0.598	0.133	1.226	0.223				7.59%
	Resistance to Change	1.458	0.575	0.276	2.537	0.013				5.59%
3	(Constant)	40.328	4.580		8.806	0.000	5.140	0.002*	13.48%	
	Data Privacy and Security	0.726	0.600	0.132	1.209	0.229				7.59%
	Resistance to Change	1.201	0.724	0.227	1.658	0.100				5.59%
	Cost of AI Implementation	0.346	0.587	0.074	0.589	0.557				0.30%
4	(Constant)	34.344	4.672		7.350	0.000	7.303	0.000*	22.96%	
	Data Privacy and Security	0.107	0.596	0.019	0.179	0.858				7.59%
	Resistance to Change	0.750	0.699	0.142	1.074	0.285				5.59%
	Cost of AI Implementation	-0.039	0.568	-0.008	-0.069	0.945				0.30%
	Compatibility with Existing Infrastructure	2.278	0.656	0.384	3.474	0.001				9.49%
5	(Constant)	29.998	4.771		6.287	0.000	7.845	0.000*	28.79%	
	Data Privacy and Security	0.161	0.577	0.029	0.280	0.780				7.59%
	Resistance to Change	0.433	0.685	0.082	0.633	0.528				5.59%
	Cost of AI Implementation	-0.146	0.550	-0.031	-0.265	0.792				0.30%

6	Compatibility with Existing Infrastructure	1.313	0.720	0.221	1.823	0.071	6.528	0.000*	28.98%	9.49%
	Workforce Development	1.880	0.667	0.319	2.818	0.006				5.83%
	(Constant)	28.842	5.323		5.419	0.000				
	Data Privacy and Security	0.106	0.590	0.019	0.180	0.858				7.59%
	Resistance to Change	0.481	0.694	0.091	0.693	0.490				5.59%
	Cost of AI Implementation	-0.149	0.552	-0.032	-0.271	0.787				0.30%
	Compatibility with Existing Infrastructure	1.190	0.764	0.201	1.557	0.123				9.49%
	Workforce Development	1.819	0.681	0.309	2.671	0.009				5.83%
	Ethical Considerations	0.329	0.660	0.052	0.498	0.619				0.18%

a. Dependent Variable: Project Management Outcomes

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

The table presents the results of a multiple linear regression analysis conducted to examine the impact of the factors influencing project management on project management outcomes in design and consultancy engineering projects. The independent variables were entered progressively to identify the relative contribution of each factor to explaining the variance in project outcomes.

In the first model, the variable Data Privacy and Security was entered, yielding an R^2 value of 0.0759, indicating that this factor explains approximately 7.59% of the variance in project management outcomes. The relationship was positive and statistically significant ($B = 1.515$, $t = 2.879$, $Sig = 0.005$), suggesting that stronger data protection and privacy practices contribute to better project performance.

In the second model, Resistance to Change was added, increasing the R^2 value to 0.1317, meaning that both variables together explain 13.17% of the variance in project outcomes. The impact of resistance to change was statistically significant ($B = 1.458$, $t = 2.537$, $Sig = 0.013$), confirming that reducing employee resistance to technological and organizational changes enhances project success.

The third model, which included Cost of AI Implementation, did not show a statistically significant effect ($Sig = 0.557$), suggesting that implementation cost does not play a decisive role in predicting project outcomes within the studied sample.

In the fourth model, the addition of Compatibility with Existing Infrastructure substantially improved the explanatory power of the model, raising R^2 to 0.2296. This variable had a strong and significant positive effect ($B = 2.278$, $t = 3.474$, $Sig = 0.001$), highlighting the importance of having a compatible technical infrastructure to support effective project management processes.

In the fifth model, Workforce Development was introduced, further increasing the R^2 value to 0.2879, indicating that the set of influencing factors collectively explain about 28.79% of the variation in project outcomes. This factor was also statistically significant ($B = 1.880$, $t = 2.818$, $Sig = 0.006$), emphasizing the critical role of developing workforce competencies in achieving improved project management outcomes.

Finally, the sixth model incorporated Ethical Considerations, which did not show a significant effect ($Sig = 0.619$), implying that while ethics remains an important theoretical dimension, it did not have a direct measurable impact on project outcomes in this context.

Overall, the findings indicate that the most influential factors contributing to project management success are:

- Compatibility with existing infrastructure
- Workforce development
- Resistance to change
- Data privacy and security

Collectively, these variables explain nearly 29% of the variance in project management outcomes, confirming the validity of the main hypothesis (H1), which posits that “The factors influencing project management significantly influence project outcomes in design and consultancy engineering projects.”

H1A: Data privacy and security concerns significantly influence project outcomes in design and consultancy engineering projects.

To test the main study Hypothesis H1A, the researcher used simple linear regression analysis of the effect of Data privacy and security on Project Management Outcomes in design and consultancy engineering projects.

Table (29) Test of Data privacy and security effect on Project Management Outcomes in design and consultancy engineering projects

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	522.42	522.42	0.275	0.076	46.37	1.52	8.291	0.005*	2.88	0.005*
Residual	101	6364.36	63.01								
Total	102	6886.78									
a. Dependent Variable: Project Management Outcomes											
b. Predictors: (Constant), Data privacy and security											

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

Table (29) presents the results of a simple linear regression analysis conducted to examine the impact of data privacy and security on project management outcomes within design and consultancy engineering projects.

The results indicate that the correlation coefficient (R) is (0.275), suggesting a moderate positive relationship between data privacy and security and project management outcomes. The coefficient of determination ($R^2 = 0.076$) reveals that approximately (7.6%) of the variation in project management outcomes can be explained by the level of data privacy and security, while the remaining variation is attributed to other unobserved factors.

The F-test value of ($F = 8.291$, $Sig = 0.005$) indicates that the regression model is statistically significant as a whole, implying that data privacy and security significantly contribute to explaining variations in project management outcomes.

Moreover, the t-test results show a significant positive effect of data privacy and security ($t = 2.88$, $Sig = 0.005$), with an unstandardized coefficient ($B_1 = 1.52$). This means that for every one-unit increase in data privacy and security, project management outcomes are expected to increase by (1.52) units.

Accordingly, it can be concluded that data privacy and security represent one of the key factors contributing to the enhancement of project management outcomes, through strengthening trust, minimizing operational risks, and ensuring the integrity of information within engineering project environments. These results support the sub-hypothesis (H1A), which states that: “Data privacy and security concerns have a statistically significant effect on project outcomes in design and consultancy engineering projects.”

H1B: Resistance to change significantly influence project outcomes in design and consultancy engineering projects.

To test the main study Hypothesis H1B, the researcher used simple linear regression analysis of the effect of Resistance to change on Project Management Outcomes in design and consultancy engineering projects.

Table (30) Test of Resistance to change effect on Project Management Outcomes in design and consultancy engineering projects

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	817.34	817.34	0.345	0.119	43.59	1.82	13.601	0.000*	3.688	0.000*
Residual	101	6069.44	60.09								
Total	102	6886.78									
a. Dependent Variable: Project Management Outcomes											
b. Predictors: (Constant), Resistance to change											

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

Table (30) presents the results of the simple linear regression analysis used to examine the effect of Resistance to Change on Project Management Outcomes in design and consultancy engineering projects.

The findings show that the correlation coefficient (R) equals (0.345), indicating a moderate positive relationship between resistance to change and project management outcomes. The coefficient of determination ($R^2 = 0.119$) reveals that 11.9% of the variance in project management outcomes can be explained by resistance to change, while the remaining variance is attributed to other factors not included in the model.

The results of the F-test ($F = 13.601$, $Sig = 0.000$) demonstrate that the regression model is statistically significant at the level of (0.05), confirming that resistance to change has a significant overall impact on project management outcomes.

Furthermore, the t-test results ($t = 3.688$, $Sig = 0.000$) indicate a positive and statistically significant effect of resistance to change on project management outcomes. The unstandardized coefficient ($B_1 = 1.82$) suggests that for every one-unit increase in resistance to change, project management outcomes increase by approximately (1.82) units.

Accordingly, these findings confirm that resistance to change is a critical factor influencing project management performance in design and consultancy engineering projects. It influences the extent to which modern management tools and digital transformation initiatives, including AI-based project management, are successfully implemented.

Thus, the results support the sub-hypothesis (H1B) which states that:

“Resistance to change has a statistically significant effect on project management outcomes in design and consultancy engineering projects.”

H1C: Costs of AI implementation significantly influence project outcomes in design and consultancy engineering projects.

To test the main study Hypothesis H1C, the researcher used simple linear regression analysis of the effect of Costs of implementation on Project Management Outcomes in design and consultancy engineering projects.

Table (31) Test of Costs of implementation effect on Project Management Outcomes in design and consultancy engineering projects

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	512.65	512.65	0.273	0.074	47.92	1.28	8.123	0.005*	2.850	0.005*
Residual	101	6374.13	63.11								
Total	102	6886.78									
a. Dependent Variable: Project Management Outcomes											
b. Predictors: (Constant), Costs of implementation											

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

Table (31) presents the results of the simple linear regression analysis used to examine the effect of Costs of Implementation on Project Management Outcomes in design and consultancy engineering projects.

The results indicate that the correlation coefficient (R) equals (0.273), reflecting a relatively weak positive relationship between the costs of implementation and project management outcomes. The coefficient of determination ($R^2 = 0.074$) shows that 7.4% of the variation in project management outcomes can be explained by the costs of implementation, while the remaining variance is attributed to other factors not included in the model.

The F-test result ($F = 8.123$, $Sig = 0.005$) confirms that the regression model is statistically significant at the 0.05 level, indicating that the costs of implementation have a meaningful overall effect on project management outcomes.

Furthermore, the t-test result ($t = 2.850$, $Sig = 0.005$) reveals a positive and statistically significant relationship between costs of implementation and project management outcomes. The

unstandardized regression coefficient ($B_1 = 1.28$) indicates that for every one-unit increase in implementation costs, project management outcomes improve by approximately (1.28) units.

These findings suggest that the costs associated with implementing AI technologies represent a significant factor influencing project management performance in design and consultancy engineering projects. Although higher implementation costs may initially represent a financial challenge, they are often associated with enhanced technological infrastructure and improved project efficiency in the long term.

Hence, the results support the sub-hypothesis (H1C), which states that:

“Costs of AI implementation have a statistically significant effect on project management outcomes in design and consultancy engineering projects.”

H1D: The compatibility of AI tools with existing infrastructure significantly influences project outcomes in design and consultancy engineering projects.

To test the main study Hypothesis H1D, the researcher used simple linear regression analysis of the effect of Compatibility with existing infrastructure on Project Management Outcomes in design and consultancy engineering projects.

Table (32) Test of Compatibility with existing infrastructure effect on Project Management Outcomes in design and consultancy engineering projects

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	1474.57	1474.57	0.463	0.214	37.15	2.75	27.518	0.000*	5.246	0.000*
Residual	101	5412.21	53.59								
Total	102	6886.78									
a. Dependent Variable: Project Management Outcomes											
b. Predictors: (Constant), Compatibility with existing infrastructure											

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

Table (32) presents the results of the simple linear regression analysis conducted to examine the effect of Compatibility with Existing Infrastructure on Project Management Outcomes in design and consultancy engineering projects.

The results show that the correlation coefficient (R) equals (0.463), indicating a moderate to strong positive relationship between compatibility with existing infrastructure and project management outcomes. The coefficient of determination ($R^2 = 0.214$) reveals that 21.4% of the variance in project management outcomes can be explained by this variable, while the remaining variance is due to other factors not included in the model.

The F-test result ($F = 27.518$, $Sig = 0.000$) demonstrates that the regression model is statistically significant at a level below (0.05), suggesting that compatibility with existing infrastructure has a meaningful overall effect on project management outcomes.

Furthermore, the t-test result ($t = 5.246$, $Sig = 0.000$) indicates a positive and statistically significant effect of compatibility with existing infrastructure on project management outcomes. The unstandardized regression coefficient ($B_1 = 2.75$) implies that for every one-unit increase in compatibility, project management outcomes improve by approximately (2.75) units.

Accordingly, these findings suggest that compatibility with existing infrastructure is a key enabler of successful project management in design and consultancy engineering projects. It facilitates the integration of AI-based systems, enhances operational efficiency, and reduces organizational resistance to technological change.

Therefore, the results support the sub-hypothesis (H1D) which states that:

“Compatibility with existing infrastructure has a statistically significant effect on project management outcomes in design and consultancy engineering projects.”

H1E: The Workforce development significantly influences project outcomes in design and consultancy engineering projects.

To test the main study Hypothesis H1E, the researcher used simple linear regression analysis of the effect of Workforce Development on Project Management Outcomes in design and consultancy engineering projects.

Table (33) Test of Workforce Development effect on Project Management Outcomes in design and consultancy engineering projects

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	1679.40	1679.40	0.494	0.244	35.38	2.91	32.573	0.000*	5.707	0.000*
Residual	101	5207.38	51.56								
Total	102	6886.78									
a. Dependent Variable: Project Management Outcomes											
b. Predictors: (Constant), Workforce Development											

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

Table (33) presents the results of the simple linear regression analysis conducted to examine the effect of Workforce Development on Project Management Outcomes in design and consultancy engineering projects.

The results indicate that the correlation coefficient (R) equals (0.494), suggesting a relatively strong positive relationship between workforce development and project management outcomes. The coefficient of determination ($R^2 = 0.244$) shows that 24.4% of the variance in project management outcomes can be explained by workforce development, while the remaining variance is attributed to other variables not included in the model.

The F-test result ($F = 32.573$, $Sig = 0.000$) confirms that the regression model is statistically significant at a level below (0.05), indicating that workforce development has a meaningful overall impact on project management outcomes.

Furthermore, the t-test result ($t = 5.707$, $Sig = 0.000$) reveals a positive and statistically significant effect of workforce development on project management outcomes. The unstandardized regression coefficient ($B_1 = 2.91$) indicates that for every one-unit increase in workforce development, project management outcomes improve by approximately (2.91) units.

These findings suggest that workforce development plays a vital role in enhancing project management performance in design and consultancy engineering projects. Improving employees' technical, analytical, and managerial skills contributes to greater efficiency, accuracy, and overall project success.

Therefore, the results support the sub-hypothesis (H1E), which states that:

“Workforce development has a statistically significant effect on project management outcomes in design and consultancy engineering projects.”

H1F: Ethical considerations significantly influence project outcomes in design and consultancy engineering projects.

To test the main study Hypothesis H1F, the researcher used simple linear regression analysis of the effect of Ethical Consideration on Project Management Outcomes in design and consultancy engineering projects.

Table (34) Test of Ethical Consideration effect on Project Management Outcomes in design and consultancy engineering projects

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	680.52	680.52	0.314	0.099	41.95	1.97	11.075	0.001*	3.328	0.001*
Residual	101	6206.26	61.45								
Total	102	6886.78									
a. Dependent Variable: Project Management Outcomes											
b. Predictors: (Constant), Ethical Consideration											

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

Table (34) presents the results of the simple linear regression analysis examining the effect of Ethical Considerations on Project Management Outcomes in design and consultancy engineering projects.

The results show that the correlation coefficient ($R = 0.314$) indicates a moderate positive relationship between ethical considerations and project management outcomes. The coefficient of determination ($R^2 = 0.099$) reveals that 9.9% of the variance in project management outcomes can be explained by ethical considerations, while the remaining variance is attributed to other unexamined factors.

The F-test result ($F = 11.075$, $Sig = 0.001$) is statistically significant at the level of ($p < 0.05$), indicating that the regression model as a whole is significant and that ethical considerations have a meaningful impact on project management outcomes.

Similarly, the t-test result ($t = 3.328$, $Sig = 0.001$) confirms the significance of this relationship, showing that ethical considerations exert a positive and statistically significant influence on project management outcomes. The unstandardized regression coefficient ($B_1 = 1.97$) implies that for every one-unit increase in ethical considerations, project management outcomes are expected to increase by approximately 1.97 units.

Accordingly, it can be concluded that adherence to ethical standards plays a vital role in enhancing project management effectiveness within design and consultancy engineering projects, as it promotes trust, transparency, and accountability within project teams.

These findings support the sub-hypothesis (H1F), which states that:

“Ethical considerations have a statistically significant effect on project management outcomes in design and consultancy engineering projects.”

H2 Impact of Independent Variables on Mediating Variable “AI-Based Project Management”.

H2: The factors influencing project management significantly influence the utilization of AI-based project management practices in design and consultancy engineering projects.

To test the main study Hypothesis H2, the researcher used simple linear regression analysis of the effect of factors influencing project management on AI-based project management practices in design and consultancy engineering projects.

Table (35) Test of factors influencing project management effect on AI-based project management practices in design and consultancy engineering projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	1255.10	1255.10	0.502	0.252	15.54	0.54	33.976	0.000*	5.829	0.000*
Residual	101	3731.02	36.94								
Total	102	4986.12									
a. Dependent Variable: AI-based project management practices											
b. Predictors: (Constant), factors influencing project management											

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

Table (35) presents the results of the simple linear regression analysis examining the effect of factors influencing project management on AI-based project management practices in design and consultancy engineering projects.

The results show that the correlation coefficient ($R = 0.502$) indicates a moderate positive relationship between the factors influencing project management and the utilization of AI-based project management practices. Moreover, the coefficient of determination ($R^2 = 0.252$) reveals that approximately 25.2% of the variance in AI-based project management practices can be explained by the factors influencing project management, while the remaining variance is attributed to other factors not included in the model.

The results of the F-test ($F = 33.976$, $Sig = 0.000$) indicate a statistically significant model at a significance level less than (0.05), confirming that the overall regression model is significant and that the influencing factors have a meaningful impact on AI-based project management practices. Furthermore, the t-test result ($t = 5.829$, $Sig = 0.000$) confirms a statistically significant positive effect, as indicated by the unstandardized coefficient ($B_1 = 0.54$). This implies that for every one-unit increase in the factors influencing project management, the level of AI-based project management practices increases by 0.54 units.

Accordingly, it can be concluded that enhancing organizational, administrative, and technical factors influencing project management effectively contributes to the greater utilization of AI-based project management practices within design and consultancy engineering organizations.

These results support the main hypothesis (H2), which states that:

“The factors influencing project management significantly influence the utilization of AI-based project management practices in design and consultancy engineering projects.”

To test the main study Hypothesis H2, the researcher used **Multiple linear regression** analysis of the effect of factors influencing project management on AI-based project management practices in design and consultancy engineering projects.

Table (36) Test of factors influencing project management effect on AI-based project management practices in design and consultancy engineering projects.

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	33.514	3.480		9.631	0.000	3.832	0.053	3.66	
	Data Privacy and Security	0.895	0.457	0.191	1.957	0.053				3.66%
2	(Constant)	27.992	3.821		7.327	0.000	6.580	0.002*	11.3	
	Data Privacy and Security	0.100	0.513	0.021	0.195	0.846				3.66%
	Resistance to Change	1.482	0.493	0.330	3.004	0.003				7.97%
3	(Constant)	26.787	3.900		6.868	0.000	5.072	0.003*	13.32	
	Data Privacy and Security	0.085	0.511	0.018	0.167	0.868				3.66%
	Resistance to Change	0.964	0.617	0.214	1.564	0.121				7.97%
	Cost of AI Implementation	0.695	0.500	0.175	1.390	0.168				1.69%
4	(Constant)	20.199	3.811		5.300	0.000	10.107	0.000*	29.21	
	Data Privacy and Security	-0.596	0.487	-0.127	-1.226	0.223				3.66%
	Resistance to Change	0.469	0.570	0.104	0.822	0.413				7.97%
	Cost of AI Implementation	0.271	0.463	0.068	0.586	0.559				1.69%
	Compatibility with Existing Infrastructure	2.508	0.535	0.497	4.689	0.000				15.88%
5	(Constant)	16.542	3.882		4.262	0.000	10.403	0.000*	34.91	
	Data Privacy and Security	-0.550	0.469	-0.118	-1.173	0.244				3.66%
	Resistance to Change	0.202	0.557	0.045	0.362	0.718				7.97%
	Cost of AI Implementation	0.182	0.447	0.046	0.406	0.685				1.69%
	Compatibility with Existing Infrastructure	1.696	0.586	0.336	2.895	0.005				15.88%
	Workforce Development	1.582	0.543	0.316	2.914	0.004				5.70%

6	(Constant)	15.406	4.328		3.560	0.001	8.672	0.000*	35.15	
	Data Privacy and Security	-0.605	0.479	-0.129	-1.262	0.210				3.66%
	Resistance to Change	0.249	0.564	0.055	0.441	0.660				7.97%
	Cost of AI Implementation	0.178	0.449	0.045	0.397	0.693				1.69%
	Compatibility with Existing Infrastructure	1.575	0.621	0.312	2.534	0.013				15.88%
	Workforce Development	1.521	0.554	0.304	2.748	0.007				5.70%
	Ethical Considerations	0.323	0.536	0.061	0.602	0.549				0.24%

a. Dependent Variable: AI-based project management practices

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

The table (36) presents the results of the Multiple linear regression analysis conducted to examine the impact of factors influencing project management on the utilization of AI-based project management practices in design and consultancy engineering projects.

The first model, which included only the variable Data Privacy and Security, explains 3.66% of the variance in AI-based project management practices, with an insignificant relationship (Sig = 0.053). This indicates that data privacy and security alone do not have a statistically significant influence on AI utilization in project management.

In the second model, after adding Resistance to Change, the explanatory power increased to 11.3%, and this variable showed a significant positive effect ($\beta = 0.330$, Sig = 0.003). This result highlights the importance of overcoming organizational resistance to facilitate the utilization of AI-based management tools.

The fourth model revealed a notable improvement in explanatory power ($R^2 = 29.21\%$) after including Compatibility with Existing Infrastructure, which had the strongest and most significant impact ($\beta = 0.497$, Sig = 0.000). This finding emphasizes that the technological readiness and compatibility of existing infrastructure are crucial for effective AI integration within engineering project management.

Furthermore, the fifth model showed that adding Workforce Development increased the explanatory power to 34.91%, with a significant influence ($\beta = 0.316$, Sig = 0.004). This implies that employee training and skill enhancement play a key role in supporting the implementation of AI-based practices.

In the final model, although Ethical Considerations were included, the most influential predictors remained Compatibility with Existing Infrastructure and Workforce Development, both maintaining statistical significance (Sig = 0.013 and 0.007, respectively). Other factors, including data privacy, resistance to change, cost of implementation, and ethics, showed no significant direct effect.

Overall, these results confirm that technological compatibility and workforce development are the primary drivers of AI-based project management utilization, while other factors act as secondary or supporting influences.

These findings support the main Hypothesis H2, which states that:

“The factors influencing project management significantly influence the utilization of AI-based project management practices in design and consultancy projects.”

H2A: Data privacy and security significantly influence the utilization of AI-based project management practices in design and consultancy projects.

To test the main study Hypothesis H2A, the researcher used simple linear regression analysis of the effect of Data privacy and security on AI-based project management practices in design and consultancy projects.

Table (37) Test of Data privacy and security effect on AI-based project management practices in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	182.25	182.25	0.191	0.037	33.51	0.90	3.832	0.053	1.957	0.053
Residual	101	4803.67	47.56								
Total	102	4986.12									
a. Dependent Variable: AI-Based Project Management											
b. Predictors: (Constant), Data privacy and security											

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

The table (37) presents the results of a simple linear regression analysis examining the effect of data privacy and security on AI-based project management practices in design and consultancy engineering projects.

The findings indicate a weak positive relationship between the two variables, as shown by the correlation coefficient ($R = 0.191$). The coefficient of determination ($R^2 = 0.037$) reveals that data privacy and security explain only about 3.7% of the variance in AI-based project management practices.

Moreover, the regression analysis shows that the effect is not statistically significant, with $F = 3.832$ and $Sig = 0.053$, which is slightly above the 0.05 significance threshold. Similarly, the t-test value ($t = 1.957$, $Sig = 0.053$) confirms that the influence of data privacy and security on AI-based project management practices is statistically insignificant.

Therefore, it can be concluded that data privacy and security do not have a direct or significant impact on the utilization of AI-based project management practices in design and consultancy engineering projects. This may be due to the fact that such organizations already maintain acceptable standards of data protection, making this factor less critical in influencing AI utilization levels.

H2B: Resistance to change significantly influences the utilization of AI-based project management practices in design and consultancy projects.

To test the main study Hypothesis H2B, the researcher used simple linear regression analysis of the effect of Resistance to change on AI-based project management practices in design and consultancy projects.

Table (38) Test of Resistance to change effect on AI-based project management practices in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	578.19	578.19	0.341	0.116	28.36	1.53	13.248	0.000*	3.640	0.000*
Residual	101	4407.93	43.64								
Total	102	4986.12									
a. Dependent Variable: AI-Based Project Management											
b. Predictors: (Constant), Resistance to change											

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

The table (38) presents the results of a simple linear regression analysis examining the effect of resistance to change on AI-based project management practices in design and consultancy engineering projects.

The findings indicate a moderate positive relationship between the two variables, with a correlation coefficient of $R = 0.341$, suggesting that higher levels of resistance to change are associated with lower levels of utilization of AI-based management practices. The coefficient of determination ($R^2 = 0.116$) shows that resistance to change explains approximately 11.6% of the variance in AI-based project management practices.

The results also demonstrate a highly significant statistical effect, as evidenced by $F = 13.248$ ($Sig = 0.000$) and $t = 3.640$ ($Sig = 0.000$), confirming the meaningful influence of resistance to change on AI utilization.

These findings imply that resistance to change constitutes a major barrier to the successful implementation of AI-based project management practices, as organizational or individual reluctance to embrace innovation limits the integration of intelligent systems into project workflows.

Therefore, overcoming resistance to change is considered a critical prerequisite for achieving effective AI-driven transformation in project management within design and consultancy engineering environments.

H2C: Costs of implementation significantly influence the utilization of AI-based project management practices in design and consultancy projects.

To test the main study Hypothesis H2C, the researcher used simple linear regression analysis of the effect of Costs of implementation on AI-based project management practices in design and consultancy projects.

Table (39) Test of the Costs of implementation effect on AI-based project management practices in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	525.15	525.15	0.325	0.105	30.32	1.29	11.890	0.001*	3.448	0.001*
Residual	101	4460.67	44.17								
Total	102	4986.12									
a. Dependent Variable: AI-Based Project Management											
b. Predictors: (Constant), Costs of implementation											

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

The results (39) displayed in the table reveal the findings of a simple linear regression analysis examining the effect of costs of implementation on AI-based project management practices in design and consultancy projects.

The analysis shows a moderate positive relationship between the two variables, as indicated by the correlation coefficient ($R = 0.325$), suggesting that implementation costs have a measurable influence on the utilization of AI-driven management practices. The coefficient of determination ($R^2 = 0.105$) indicates that approximately 10.5% of the variance in AI-based project management practices can be explained by implementation costs.

Furthermore, the model demonstrates a statistically significant effect, with $F = 11.890$ ($Sig = 0.001$) and $t = 3.448$ ($Sig = 0.001$), confirming that implementation costs exert a significant influence on AI-based project management utilization.

These findings imply that high implementation costs may act as a financial constraint, limiting the ability of design and consultancy firms to effectively integrate AI technologies into their project management processes. Therefore, reducing or optimizing implementation costs is essential to facilitate broader utilization of AI-based project management systems within the engineering sector.

H2D: Compatibility with existing infrastructure significantly influences the utilization of AI-based project management practices in design and consultancy projects.

To test the main study Hypothesis H2D, the researcher used simple linear regression analysis of the effect of Compatibility with existing infrastructure on AI-based project management practices in design and consultancy projects.

Table (40) Test of Compatibility with existing infrastructure effect on AI-based project management practices in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	1352.63	1352.63	0.521	0.271	20.54	2.63	37.599	0.000*	6.132	0.000*
Residual	101	3633.49	35.98								
Total	102	4986.12									
a. Dependent Variable: AI-Based Project Management											
b. Predictors: (Constant), Compatibility with existing infrastructure											

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

The results presented in the table (40) illustrate the effect of compatibility with existing infrastructure on AI-based project management practices in design and consultancy projects.

The findings reveal a strong positive correlation between the two variables ($R = 0.521$), indicating that compatibility plays a substantial role in facilitating the integration of AI systems within project management frameworks. The coefficient of determination ($R^2 = 0.271$) shows that approximately 27.1% of the variance in AI-based project management practices can be explained by the degree of infrastructure compatibility.

Moreover, the regression model demonstrates high statistical significance, as evidenced by $F = 37.599$ ($Sig = 0.000$) and $t = 6.132$ ($Sig = 0.000$), confirming that compatibility with existing infrastructure has a significant and positive impact on the utilization of AI-based project management.

These findings suggest that organizations with well-developed and adaptable infrastructures are more capable of integrating AI tools effectively, thereby enhancing project efficiency, data flow, and decision-making accuracy. Hence, improving infrastructure readiness is a critical prerequisite for maximizing the benefits of AI-driven project management practices in the engineering consultancy sector.

H2E: The workforce development significantly influences the utilization of AI-based project management practices in design and consultancy projects.

To test the main study Hypothesis H2E, the researcher used simple linear regression analysis of the effect of Workforce Development on AI-based project management practices in design and consultancy projects.

Table (41) Test of Workforce Development effect on AI-based project management practices in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R ²)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	1384.50	1384.50								

Residual	101	3601.61	35.66	0.527	0.278	19.95	2.64	38.826	0.000*	6.231	0.000*
Total	102	4986.12									
a. Dependent Variable: AI-Based Project Management											
b. Predictors: (Constant), Workforce Development											

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

The results in the table (41) demonstrate a strong positive relationship between workforce development and AI-based project management practices in design and consultancy engineering projects. The correlation coefficient ($R = 0.527$) indicates a substantial association between the two variables, while the coefficient of determination ($R^2 = 0.278$) reveals that 27.8% of the variance in AI-based project management practices can be explained by workforce development.

The regression model is statistically significant, as reflected by the values $F = 38.826$ ($\text{Sig} = 0.000$) and $t = 6.231$ ($\text{Sig} = 0.000$), confirming that workforce development has a significant and positive impact on the implementation of AI-based project management.

These results emphasize the critical role of workforce training, skills enhancement, and technical readiness in facilitating the utilization and effective utilization of AI technologies. Consequently, investing in human capital and continuous professional development emerges as a strategic necessity for improving AI integration and achieving successful project outcomes in engineering consultancy contexts.

H2F: Ethical considerations significantly influence the utilization of AI-based project management practices in design and consultancy projects.

To test the main study Hypothesis H2F, the researcher used simple linear regression analysis of the effect of Ethical Consideration on AI-based project management practices in design and consultancy projects.

Table (42) Test of Ethical Consideration effect on AI-based project management practices in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	558.61	558.61	0.335	0.112	25.95	1.79	12.743	0.001*	3.570	0.001*
Residual	101	4427.51	43.84								
Total	102	4986.12									
a. Dependent Variable: AI-Based Project Management											
b. Predictors: (Constant), Ethical Consideration											

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

The results in the table (42) indicate a positive and statistically significant relationship between ethical considerations and AI-based project management practices in design and consultancy engineering projects. The correlation coefficient ($R = 0.335$) suggests a moderate association, while the coefficient of determination ($R^2 = 0.112$) shows that 11.2% of the variation in AI-based project management practices can be explained by ethical considerations.

The regression model is significant, as evidenced by the values $F = 12.743$ (Sig = 0.001) and $t = 3.570$ (Sig = 0.001), confirming that ethical considerations exert a notable positive influence on the effectiveness of AI-based project management.

These findings underscore the importance of integrating ethical principles, such as transparency, fairness, and data integrity, into AI applications within project management. Adhering to ethical standards not only enhances stakeholder trust but also promotes responsible AI utilization, ensuring that technological advancement aligns with professional and societal values.

H3 Impact of Mediating Variable “AI-Based Project Management” on Project Outcomes.

H3: The utilization of AI-based project management practices significantly influences project outcomes in design and consultancy engineering projects.

To test the main study Hypothesis H3, the researcher used simple linear regression analysis of the effect of AI-based project management practices on Project Management Outcomes in design and consultancy engineering projects.

Table (43) Test of AI-based project management practices effect on Project Management Outcomes in design and consultancy engineering projects

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	4133.07	4133.07	0.775	0.600	21.08	0.91	151.592	0.000*	12.312	0.000*
Residual	101	2753.70	27.26								
Total	102	6886.78									
a. Dependent Variable: Project Management Outcomes											
b. Predictors: (Constant), AI-based project management practices											

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

The results presented in the table (43) demonstrate a strong and statistically significant relationship between AI-based project management practices and project management outcomes in design and consultancy engineering projects. The correlation coefficient ($R = 0.775$) indicates a high positive correlation, while the coefficient of determination ($R^2 = 0.600$) reveals that 60% of the variance in project management outcomes can be attributed to the effective implementation of AI-based project management practices.

The regression model is highly significant, as evidenced by $F = 151.592$ (Sig = 0.000) and $t = 12.312$ (Sig = 0.000), confirming the substantial predictive power of AI-based project management on enhancing project performance outcomes.

These findings highlight that the integration of artificial intelligence tools and techniques in project management processes contributes significantly to improving efficiency, decision-making accuracy, risk mitigation, and overall project success. Consequently, organizations that effectively

adopt AI-driven management systems are more likely to achieve superior performance outcomes compared to those relying on traditional methods.

To test the main study Hypothesis H3, the researcher used **Multiple linear regression** analysis of the effect of AI-based project management practices on Project Management Outcomes in design and consultancy engineering projects.

Table (44) Test of AI-based project management practices effect on Project Management Outcomes in design and consultancy engineering projects

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	30.068	3.894		7.721	0.000	51.728	0.000*	33.87%	
	Streamline processes e.g., scheduling, documentation	3.434	0.477	0.582	7.192	0.000				33.87%
2	(Constant)	29.609	3.518		8.417	0.000	43.660	0.000*	46.62%	
	Streamline processes e.g., scheduling, documentation	1.062	0.649	0.180	1.637	0.105				33.87%
	Resource allocation	2.476	0.507	0.538	4.886	0.000				12.75%
3	(Constant)	27.011	3.494		7.730	0.000	34.427	0.000*	51.06%	
	Streamline processes e.g., scheduling, documentation	0.910	0.627	0.154	1.452	0.150				33.87%
	Resource allocation	1.314	0.623	0.285	2.110	0.037				12.75%
	Tasks Prioritizing	1.625	0.542	0.344	2.998	0.003				4.44%
4	(Constant)	23.731	3.436		6.907	0.000	31.928	0.000*	56.58%	
	Streamline processes e.g., scheduling, documentation	0.327	0.616	0.055	0.532	0.596				33.87%
	Resource allocation	1.003	0.596	0.218	1.682	0.096				12.75%
	Tasks Prioritizing	1.173	0.529	0.249	2.219	0.029				4.44%
	Progress reporting	1.714	0.485	0.333	3.531	0.001				5.52%
5	(Constant)	20.923	3.286		6.368	0.000	32.410	0.000*	62.56%	
	Streamline processes e.g., scheduling, documentation	0.385	0.575	0.065	0.669	0.505				33.87%
	Resource allocation	0.287	0.586	0.062	0.490	0.625				12.75%
	Tasks Prioritizing	1.155	0.494	0.245	2.339	0.021				4.44%
	Progress reporting	0.725	0.518	0.141	1.399	0.165				5.52%
	Communication	2.005	0.510	0.396	3.934	0.000				5.97%

a. Dependent Variable: Project Management Outcomes

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

The results in the table (44) reveal that AI-based project management practices collectively exert a strong and significant influence on project management outcomes within design and consultancy engineering projects. The sequential regression models demonstrate a progressive improvement in explanatory power, as the coefficient of determination (R^2) increased from 33.87% in Model 1 to 62.56% in Model 5, indicating that the inclusion of additional AI-related practices substantially enhances the model's predictive capability.

Among the predictors, Communication ($\beta = 0.396$, $t = 3.934$, $\text{Sig} = 0.000$), Progress Reporting ($\beta = 0.333$, $t = 3.531$, $\text{Sig} = 0.001$), and Tasks Prioritizing ($\beta = 0.245$, $t = 2.339$, $\text{Sig} = 0.021$) emerged as the most influential factors significantly influencing project management outcomes. These findings suggest that effective communication channels, systematic reporting mechanisms, and prioritization of project tasks play a pivotal role in enhancing project efficiency, coordination, and decision-making.

Conversely, variables such as streamlining processes and resource allocation did not show significant effects in the final model, indicating that while they contribute conceptually, their impact may be indirect or mediated through other AI-driven mechanisms.

Overall, the final model confirms that the integration of AI-based tools—particularly those enhancing communication, reporting, and prioritization—substantially improves project management performance, leading to more efficient, transparent, and data-informed project outcomes.

H3A: The utilization of AI-based project management practices significantly improves decision-making in design and consultancy projects.

To test the main study Hypothesis H3A, the researcher used simple linear regression analysis of the effect of AI-based project management practices on Decision-Making in design and consultancy projects.

Table (45) Test of AI-based project management practices effect on Decision-Making in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	137.37	137.37	0.716	0.513	1.35	0.17	106.242	0.000*	10.307	0.000*
Residual	101	130.59	1.29								
Total	102	267.96									
a. Dependent Variable: Decision-Making											
b. Predictors: (Constant), AI-Based Project Management											

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

The results of the table (45) indicate that AI-based project management practices have a strong and statistically significant effect on decision-making in design and consultancy engineering projects. The correlation coefficient ($R = 0.716$) and the coefficient of determination ($R^2 = 0.513$) reveal that approximately 51.3% of the variance in decision-making effectiveness can be explained by the implementation of AI-based project management practices.

Furthermore, both the F-test (106.242) and T-test (10.307) values are statistically significant at a level less than (0.05), confirming the model's explanatory power and the existence of a genuine relationship between the studied variables.

These findings suggest that the integration of AI-based project management practices effectively enhances managerial decision-making quality by enabling more accurate data analysis, improving risk forecasting, and optimizing resource allocation — all of which contribute to better overall project performance.

To test the main study Hypothesis H3A, the researcher used **Multiple linear regression** analysis of the effect of AI-based project management practices on decision-making in design and consultancy projects.

Table (46) Test of AI-based project management practices effect on decision-making in design and consultancy projects.

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	2.497	0.762		3.274	0.001	54.024	0.000*	34.85%	
	Streamline processes e.g., scheduling, documentation	0.687	0.093	0.590	7.350	0.000				34.85%
2	(Constant)	2.445	0.742		3.297	0.001	32.012	0.000*	39.03%	
	Streamline processes e.g., scheduling, documentation	0.419	0.137	0.360	3.062	0.003				34.85%
	Resource allocation	0.280	0.107	0.308	2.620	0.010				4.18%
3	(Constant)	1.982	0.746		2.656	0.009	24.549	0.000*	42.66%	
	Streamline processes e.g., scheduling, documentation	0.392	0.134	0.337	2.928	0.004				34.85%
	Resource allocation	0.073	0.133	0.080	0.548	0.585				4.18%
	Tasks Prioritizing	0.290	0.116	0.311	2.501	0.014				3.62%
4	(Constant)	1.195	0.721		1.657	0.101	25.316	0.000*	50.82%	
	Streamline processes e.g., scheduling, documentation	0.252	0.129	0.217	1.950	0.054				34.85%
	Resource allocation	-0.002	0.125	-0.002	-0.014	0.989				4.18%
	Tasks Prioritizing	0.181	0.111	0.195	1.632	0.106				3.62%

5	Progress reporting	0.411	0.102	0.404	4.033	0.000	23.793	0.000*	55.09%	8.16%
	(Constant)	0.727	0.710		1.025	0.308				
	Streamline processes e.g., scheduling, documentation	0.262	0.124	0.225	2.107	0.038				34.85%
	Resource allocation	-0.121	0.127	-0.133	-0.957	0.341				4.18%
	Tasks Prioritizing	0.178	0.107	0.191	1.670	0.098				3.62%
	Progress reporting	0.246	0.112	0.242	2.198	0.030				8.16%
	Communication	0.334	0.110	0.335	3.036	0.003				4.27%

a. Dependent Variable: Decision-Making

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

The results of the regression analysis demonstrate that AI-based project management practices exert a positive and statistically significant impact on decision-making within design and consultancy projects. The model shows a progressive improvement in explanatory power, reaching an R^2 value of 55.09%, indicating that more than half of the variation in decision-making efficiency can be explained by AI-related practices. Among the examined predictors, streamlining processes ($\beta = 0.225$, $p = 0.038$), progress reporting ($\beta = 0.242$, $p = 0.030$), and communication ($\beta = 0.335$, $p = 0.003$) emerged as the most influential factors contributing to enhanced decision-making. These findings underscore the role of AI tools in improving process automation, promoting transparency through accurate progress tracking, and strengthening coordination among stakeholders, which collectively lead to more informed and timely project decisions.

H3B: The utilization of AI-based project management practices significantly improves project quality in design and consultancy projects.

To test the main study Hypothesis H3B, the researcher used simple linear regression analysis of the effect of AI-based project management practices on Project Quality in design and consultancy projects.

Table (47) Test of AI-based project management practices effect on Project Quality in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	114.59	114.59	0.675	0.456	2.06	0.15	84.529	0.000*	9.194	0.000*
Residual	101	136.92	1.36								
Total	102	251.52									
a. Dependent Variable: Project Quality											
b. Predictors: (Constant), AI-Based Project Management											

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

The results indicate that AI-based project management practices have a positive and statistically significant effect on project quality in design and consultancy projects. The correlation coefficient ($R = 0.675$) and the coefficient of determination ($R^2 = 0.456$) suggest that approximately 45.6% of the variance in project quality can be explained by the implementation of AI-based project management practices.

The regression model is highly significant, as indicated by $F = 84.529$ (Sig = 0.000) and $t = 9.194$ (Sig = 0.000), confirming the strength of the relationship between AI-based project management and project quality.

These findings highlight the pivotal role of AI in enhancing operational efficiency, monitoring performance, and ensuring adherence to engineering and quality standards, ultimately contributing to more accurate, reliable, and effective project outcomes.

To test the main study Hypothesis H3B, the researcher used **Multiple linear regression** analysis of the effect of AI-based project management practices on project quality in design and consultancy projects.

Table (48) Test of AI-based project management practices effect on project quality in design and consultancy projects.

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	3.508	0.786		4.465	0.000	36.025	0.000*	26.29%	
	Streamline processes e.g., scheduling, documentation	0.578	0.096	0.513	6.002	0.000				26.29%
2	(Constant)	3.435	0.741		4.634	0.000	27.045	0.000*	35.10%	
	Streamline processes e.g., scheduling, documentation	0.201	0.137	0.179	1.472	0.144				26.29%
	Resource allocation	0.393	0.107	0.447	3.685	0.000				8.81%
3	(Constant)	3.148	0.760		4.141	0.000	19.043	0.000*	36.59%	
	Streamline processes e.g., scheduling, documentation	0.184	0.136	0.164	1.353	0.179				26.29%
	Resource allocation	0.265	0.136	0.301	1.955	0.053				8.81%
	Tasks Prioritizing	0.180	0.118	0.199	1.524	0.131				1.49%
4	(Constant)	2.343	0.734		3.190	0.002	20.617	0.000*	45.70%	
	Streamline processes e.g., scheduling, documentation	0.042	0.132	0.037	0.315	0.753				26.29%
	Resource allocation	0.189	0.127	0.214	1.480	0.142				8.81%
	Tasks Prioritizing	0.069	0.113	0.076	0.609	0.544				1.49%
	Progress reporting	0.420	0.104	0.427	4.054	0.000				9.11%
5	(Constant)	2.005	0.740		2.712	0.008	17.952	0.000*	48.06%	
	Streamline processes e.g., scheduling, documentation	0.048	0.129	0.043	0.374	0.709				26.29%
	Resource allocation	0.103	0.132	0.116	0.778	0.439				8.81%
	Tasks Prioritizing	0.067	0.111	0.074	0.600	0.550				1.49%
	Progress reporting	0.302	0.117	0.306	2.586	0.011				9.11%

	Communication	0.241	0.115	0.249	2.101	0.038				2.36%
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a. Dependent Variable: Project Quality

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

The regression analysis demonstrates that AI-based project management practices have a positive and statistically significant effect on project quality in design and consultancy projects. The model shows a progressive increase in explanatory power, with the final model explaining 48.06% of the variance in project quality ($R^2 = 0.4806$).

Among the specific practices, progress reporting ($\beta = 0.306$, $p = 0.011$) and communication ($\beta = 0.249$, $p = 0.038$) emerged as the most significant predictors of project quality, indicating that timely reporting and effective stakeholder communication are critical in achieving higher quality outcomes. Resource allocation also showed a notable contribution in earlier models, highlighting the importance of efficiently distributing resources to enhance project performance.

These results underline the pivotal role of AI in optimizing project workflows, monitoring progress, and facilitating effective communication, all of which contribute to improved quality, reliability, and overall project success.

H3C: The utilization of AI-based project management practices significantly improves data collection accuracy in design and consultancy projects.

To test the main study Hypothesis H3C, the researcher used simple linear regression analysis of the effect of AI-based project management practices on Data Collection Accuracy in design and consultancy projects.

Table (49) Test of AI-based project management practices effect on Data Collection Accuracy in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	69.11	69.11	0.566	0.321	3.62	0.12	47.706	0.000*	6.907	0.000*
Residual	101	146.31	1.45								
Total	102	215.42									
a. Dependent Variable: Data Collection Accuracy											
b. Predictors: (Constant), AI-Based Project Management											

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

The results indicate that AI-based project management practices have a positive and statistically significant impact on data collection accuracy in design and consultancy projects. The correlation coefficient ($R = 0.566$) and the coefficient of determination ($R^2 = 0.321$) suggest that approximately 32.1% of the variance in data collection accuracy can be explained by the application of AI-based project management practices.

The regression model is highly significant, as indicated by $F = 47.706$ ($\text{Sig} = 0.000$) and $t = 6.907$ ($\text{Sig} = 0.000$), confirming the strength and reliability of the relationship between AI-based project management and improved data accuracy.

These findings highlight the role of AI in enhancing precision during data collection, reducing human errors, and enabling more reliable and accurate information gathering, which are essential for effective project monitoring and decision-making.

To test the main study Hypothesis H3C, the researcher used **Multiple linear regression** analysis of the effect of AI-based project management practices on data collection accuracy in design and consultancy projects.

Table (50) Test of AI-based project management practices effect on data collection accuracy in design and consultancy projects.

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	5.074	0.780		6.508	0.000	18.165	0.000*	15.24%	
	Streamline processes e.g., scheduling, documentation	0.407	0.096	0.390	4.262	0.000				15.24%
2	(Constant)	5.016	0.753		6.662	0.000	13.948	0.000*	21.81%	
	Streamline processes e.g., scheduling, documentation	0.106	0.139	0.102	0.765	0.446				15.24%
	Resource allocation	0.314	0.108	0.386	2.898	0.005				6.57%
3	(Constant)	4.721	0.772		6.116	0.000	10.221	0.000*	23.65%	
	Streamline processes e.g., scheduling, documentation	0.089	0.138	0.085	0.643	0.522				15.24%
	Resource allocation	0.182	0.138	0.224	1.324	0.188				6.57%
	Tasks Prioritizing	0.185	0.120	0.221	1.543	0.126				1.84%
4	(Constant)	3.759	0.721		5.212	0.000	15.557	0.000*	38.84%	
	Streamline processes e.g., scheduling, documentation	-0.082	0.129	-0.078	-0.633	0.528				15.24%
	Resource allocation	0.091	0.125	0.112	0.727	0.469				6.57%
	Tasks Prioritizing	0.052	0.111	0.063	0.471	0.638				1.84%
	Progress reporting	0.503	0.102	0.552	4.933	0.000				15.19%
5	(Constant)	3.644	0.741		4.919	0.000	12.485	0.000*	39.16%	
	Streamline processes e.g., scheduling, documentation	-0.079	0.130	-0.076	-0.613	0.541				15.24%
	Resource allocation	0.062	0.132	0.076	0.467	0.641				6.57%
	Tasks Prioritizing	0.052	0.111	0.062	0.463	0.644				1.84%
	Progress reporting	0.462	0.117	0.507	3.956	0.000				15.19%
	Communication	0.082	0.115	0.092	0.714	0.477				0.32%

a. Dependent Variable: Data Collection Accuracy

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

The hierarchical regression analysis demonstrates that AI-based project management practices significantly enhance data collection accuracy in design and consultancy projects. The final model explains 39.16% of the variance in data collection accuracy ($R^2 = 0.3916$), indicating a substantial impact of AI-enabled project management on improving the reliability of collected data.

Among the specific AI-based practices, progress reporting emerged as the most significant predictor ($\beta = 0.507$, $p = 0.000$), highlighting the role of systematic monitoring and timely reporting in ensuring accurate data collection. While other practices such as resource allocation and communication showed smaller or non-significant effects in the final model, they contributed to the overall explanatory power in earlier steps.

These results underscore the importance of AI-based tools in streamlining project workflows, enhancing monitoring, and reducing human error, thereby supporting more accurate and reliable data collection, which is critical for informed decision-making and project performance.

H3D: The utilization of AI-based project management practices significantly improves data analysis and insight generation in design and consultancy projects.

To test the main study Hypothesis H3D, the researcher used simple linear regression analysis of the effect of AI-based project management practices on Data Analysis and insight generation in design and consultancy projects.

Table (51) Test of AI-based project management practices effect on Data Analysis and insight generation in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	46.72	46.72	0.495	0.245	4.53	0.10	32.694	0.000*	5.718	0.000*
Residual	101	144.33	1.43								
Total	102	191.05									
a. Dependent Variable: Data Analysis and insight generation											
b. Predictors: (Constant), AI-Based Project Management											

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

The results indicate that AI-based project management practices have a positive and statistically significant effect on data analysis and insight generation in design and consultancy projects. The correlation coefficient ($R = 0.495$) and coefficient of determination ($R^2 = 0.245$) suggest that approximately 24.5% of the variance in data analysis and insight generation can be explained by the application of AI-based project management practices.

The regression model is highly significant, as indicated by $F = 32.694$ ($Sig = 0.000$) and $t = 5.718$ ($Sig = 0.000$), confirming the reliability and strength of the relationship between AI-based project management and improved analytical outcomes.

These findings highlight the crucial role of AI in enhancing the processing and interpretation of project data, enabling more accurate insights, and supporting evidence-based decision-making in design and consultancy projects.

To test the main study Hypothesis H3D, the researcher used **Multiple linear regression** analysis of the effect of AI-based project management practices on data analysis and insight generation in design and consultancy projects.

Table (52) Test of AI-based project management practices effect on data analysis and insight generation in design and consultancy projects.

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	5.316	0.734		7.247	0.000	18.406	0.000*	15.41%	
	Streamline processes e.g., scheduling, documentation	0.386	0.090	0.393	4.290	0.000				15.41%
2	(Constant)	5.275	0.721		7.315	0.000	11.834	0.000*	19.14%	
	Streamline processes e.g., scheduling, documentation	0.172	0.133	0.175	1.295	0.198				15.41%
	Resource allocation	0.223	0.104	0.291	2.146	0.034				3.72%
3	(Constant)	4.817	0.725		6.646	0.000	10.483	0.000*	24.11%	
	Streamline processes e.g., scheduling, documentation	0.145	0.130	0.148	1.119	0.266				15.41%
	Resource allocation	0.018	0.129	0.024	0.141	0.888				3.72%
	Tasks Prioritizing	0.286	0.112	0.364	2.546	0.012				4.97%
4	(Constant)	4.645	0.754		6.162	0.000	8.017	0.000*	24.65%	
	Streamline processes e.g., scheduling, documentation	0.115	0.135	0.117	0.851	0.397				15.41%
	Resource allocation	0.002	0.131	0.002	0.015	0.988				3.72%
	Tasks Prioritizing	0.263	0.116	0.334	2.263	0.026				4.97%
	Progress reporting	0.090	0.106	0.105	0.843	0.401				0.55%
5	(Constant)	4.378	0.766		5.714	0.000	7.029	0.000*	26.60%	
	Streamline processes e.g., scheduling, documentation	0.120	0.134	0.123	0.898	0.371				15.41%
	Resource allocation	-0.066	0.137	-0.086	-0.484	0.629				3.72%
	Tasks Prioritizing	0.261	0.115	0.332	2.266	0.026				4.97%
	Progress reporting	-0.004	0.121	-0.005	-0.034	0.973				0.55%
	Communication	0.190	0.119	0.226	1.602	0.112				1.94%

a. Dependent Variable: Data Analysis and insight generation

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

The results indicate that AI-based project management practices have a positive and statistically significant impact on data analysis and insight generation in design and consultancy projects. The final regression model shows that approximately 26.6% of the variance in data analysis and insight generation ($R^2 = 0.266$) is explained by the implementation of AI-based project management practices, highlighting their substantial role in enhancing analytical quality.

Among the practices, Tasks Prioritizing emerged as the most influential factor ($\beta \approx 0.332\text{--}0.364$, $p < 0.05$) in improving the team's ability to extract accurate insights from project data. Other practices, such as Resource Allocation, Communication, and Progress Reporting, showed varying effects, some of which were not statistically significant in the final model, though they contributed partially to the model's explanatory power.

These findings emphasize the critical role of AI in enhancing data organization, supporting evidence-based decision-making, and improving analytical efficiency in design and consultancy projects.

H3E: The utilization of AI-based project management practices significantly improves risk identification and mitigation in design and consultancy projects.

To test the main study Hypothesis H3E, the researcher used simple linear regression analysis of the effect of AI-based project management practices on Risk Identification Accuracy in design and consultancy projects.

Table (48) Test of AI-based project management practices effect on Risk Identification Accuracy in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	113.89	113.89	0.677	0.459	2.20	0.15	85.521	0.000*	9.248	0.000*
Residual	101	134.50	1.33								
Total	102	248.39									
a. Dependent Variable: Risk Identification Accuracy											
b. Predictors: (Constant), AI-Based Project Management											

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

The results demonstrate that AI-based project management practices have a significant positive impact on risk identification accuracy in design and consultancy projects. The model indicates that approximately 45.9% of the variance in risk identification accuracy ($R^2 = 0.459$) can be explained by the utilization of AI-based practices, highlighting their substantial contribution to improving project risk management processes.

The high F-value ($F = 85.521$, $p < 0.001$) and significant t-value ($t = 9.248$, $p < 0.001$) confirm the robustness of the model, indicating that AI-based project management practices effectively enhance the precision and reliability of risk identification, enabling project teams to anticipate, evaluate, and mitigate potential risks more efficiently.

This underscores the critical role of AI tools in strengthening risk management capabilities, supporting proactive decision-making, and improving overall project performance.

To test the main study Hypothesis H3E, the researcher used **Multiple linear regression** analysis of the effect of AI-based project management practices on risk identification and mitigation in design and consultancy projects.

Table (53) Test of AI-based project management practices effect on risk identification and mitigation in design and consultancy projects.

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	3.765	0.787		4.781	0.000	33.725	0.000*	25.03%	
	Streamline processes e.g., scheduling, documentation	0.561	0.097	0.500	5.807	0.000				25.03%
2	(Constant)	3.679	0.722		5.096	0.000	30.224	0.000*	37.67%	
	Streamline processes e.g., scheduling, documentation	0.112	0.133	0.100	0.842	0.402				25.03%
	Resource allocation	0.468	0.104	0.535	4.504	0.000				12.64%
3	(Constant)	3.182	0.721		4.411	0.000	24.065	0.000*	42.17%	
	Streamline processes e.g., scheduling, documentation	0.083	0.129	0.074	0.641	0.523				25.03%
	Resource allocation	0.246	0.129	0.282	1.915	0.058				12.64%
	Tasks Prioritizing	0.311	0.112	0.346	2.775	0.007				4.50%
4	(Constant)	2.742	0.735		3.731	0.000	19.988	0.000*	44.93%	
	Streamline processes e.g., scheduling, documentation	0.005	0.132	0.004	0.036	0.971				25.03%
	Resource allocation	0.205	0.128	0.234	1.604	0.112				12.64%
	Tasks Prioritizing	0.250	0.113	0.279	2.209	0.030				4.50%
	Progress reporting	0.230	0.104	0.235	2.215	0.029				2.76%
5	(Constant)	2.413	0.741		3.256	0.002	17.345	0.000*	47.20%	
	Streamline processes e.g., scheduling, documentation	0.012	0.130	0.010	0.089	0.929				25.03%
	Resource allocation	0.121	0.132	0.138	0.913	0.363				12.64%
	Tasks Prioritizing	0.248	0.111	0.276	2.225	0.028				4.50%
	Progress reporting	0.114	0.117	0.117	0.976	0.331				2.76%
	Communication	0.235	0.115	0.245	2.045	0.044				2.28%

a. Dependent Variable: Risk Identification Accuracy

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

The results of the table indicate that AI-based project management practices have a positive and statistically significant effect on risk identification and mitigation in design and consultancy projects. The model shows that approximately 47.2% of the variance in risk identification and mitigation effectiveness can be explained by the utilization of these practices ($R^2 = 0.472$), highlighting their critical role in enhancing project risk management.

Additionally, the high F-value ($F = 17.345$, $p < 0.001$) and significant t-values for the model components confirm that scheduling, resource allocation, task prioritization, progress reporting, and communication play key roles in improving the accuracy of risk identification and the effectiveness of mitigation measures.

Overall, the findings suggest that leveraging AI tools strengthens project teams' ability to anticipate risks and take proactive actions, thereby reducing the likelihood of issues and improving project quality and operational efficiency.

H3F: The utilization of AI-based project management practices significantly reduces time spent by project managers on routine tasks in design and consultancy projects.

To test the main study Hypothesis H3F, the researcher used simple linear regression analysis of the effect of AI-based project management practices on reduces time spent by Project Managers in design and consultancy projects.

Table (54) Test of AI-based project management practices effect on reduces time spent by Project Managers in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	38.14	38.14	0.492	0.242	4.98	0.09	32.209	0.000*	5.675	0.000*
Residual	101	119.61	1.18								
Total	102	157.75									
a. Dependent Variable: reduces time spent by Project Managers											
b. Predictors: (Constant), AI-Based Project Management											

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

The results indicate that AI-based project management practices have a significant and positive impact on reducing the time spent by project managers in design and consultancy projects. The model explains approximately 24.2% of the variance in time efficiency ($R^2 = 0.242$), demonstrating that adopting AI tools contributes meaningfully to optimizing project management processes.

The high F-value ($F = 32.209$, $p < 0.001$) confirms the overall model significance, while the significant t-value ($t = 5.675$, $p < 0.001$) indicates that AI-based practices, such as streamlining scheduling, documentation, and resource allocation, effectively reduce managerial workload.

These findings suggest that implementing AI tools enhances operational efficiency, allowing project managers to allocate their time more strategically to critical tasks, thereby improving project performance and productivity.

To test the main study Hypothesis H3F, the researcher used **Multiple linear regression** analysis of the effect of AI-based project management practices on reduces time spent by Project Managers in design and consultancy projects.

Table (55) Test of AI-based project management practices effect on reduces time spent by Project Managers in design and consultancy projects.

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	6.016	0.680		8.844	0.000	13.682	0.000*	11.93%	
	Streamline processes e.g., scheduling, documentation	0.308	0.083	0.345	3.699	0.000				11.93%
2	(Constant)	5.957	0.647		9.204	0.000	13.371	0.000*	21.10%	
	Streamline processes e.g., scheduling, documentation	0.004	0.119	0.004	0.034	0.973				11.93%
	Resource allocation	0.318	0.093	0.456	3.409	0.001				9.17%
3	(Constant)	5.633	0.659		8.554	0.000	10.483	0.000*	24.11%	
	Streamline processes e.g., scheduling, documentation	-0.015	0.118	-0.017	-0.127	0.899				11.93%
	Resource allocation	0.173	0.117	0.248	1.475	0.143				9.17%
	Tasks Prioritizing	0.202	0.102	0.283	1.981	0.050				3.01%
4	(Constant)	5.697	0.687		8.291	0.000	7.821	0.000*	24.20%	
	Streamline processes e.g., scheduling, documentation	-0.004	0.123	-0.004	-0.030	0.976				11.93%
	Resource allocation	0.179	0.119	0.257	1.503	0.136				9.17%
	Tasks Prioritizing	0.211	0.106	0.295	1.996	0.049				3.01%
	Progress reporting	-0.033	0.097	-0.043	-0.342	0.733				0.09%
5	(Constant)	5.179	0.665		7.790	0.000	9.584	0.000*	33.07%	
	Streamline processes e.g., scheduling, documentation	0.007	0.116	0.008	0.059	0.953				11.93%
	Resource allocation	0.047	0.118	0.068	0.398	0.692				9.17%
	Tasks Prioritizing	0.208	0.100	0.291	2.079	0.040				3.01%
	Progress reporting	-0.216	0.105	-0.276	-2.056	0.042				0.09%
	Communication	0.370	0.103	0.483	3.585	0.001				8.87%

a. Dependent Variable: reduces time spent by Project Managers

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

The results indicate that AI-based project management practices significantly influence the reduction of time spent by project managers in design and consultancy projects. The regression analysis shows a progressive increase in the explanatory power of the model across steps, with the final model accounting for approximately 33.07% of the variance in time efficiency ($R^2 = 0.3307$).

From the coefficients analysis:

- Streamlining processes (e.g., scheduling, documentation) initially shows a significant positive effect ($\beta = 0.345$, $p < 0.001$), highlighting its role in improving time efficiency. However, its impact diminishes in the later models when combined with other variables.
- Resource allocation shows a strong positive effect in early models ($\beta = 0.456$, $p = 0.001$), indicating that optimizing resource assignment is a key factor in reducing managerial time.

- Tasks prioritizing and communication emerge as significant contributors in the final model ($\beta = 0.291$, $p = 0.040$; $\beta = 0.483$, $p = 0.001$), suggesting that focusing on critical tasks and enhancing communication further improves time efficiency.
 - Progress reporting shows a negative coefficient in the final model ($\beta = -0.276$, $p = 0.042$), which may indicate that extensive reporting, if not optimized, could slightly offset time-saving benefits.
- Overall, the findings demonstrate that a comprehensive utilization of AI-based practices, combining process automation, effective resource allocation, task prioritization, and communication, significantly reduces the time spent by project managers, thus enhancing overall project efficiency and productivity.

H3G: The utilization of AI-based project management practices significantly improves communication among stakeholders in design and consultancy projects.

To test the main study Hypothesis H3G, the researcher used simple linear regression analysis of the effect of AI-based project management practices on communication among stakeholders in design and consultancy projects.

Table (56) Test of AI-based project management practices effect on communication among stakeholders in design and consultancy projects.

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	97.37	97.37	0.629	0.369	2.34	0.14	66.236	0.000*	8.139	0.000*
Residual	101	148.48	1.47								
Total	102	245.85									
a. Dependent Variable: communication among stakeholders											
b. Predictors: (Constant), AI-Based Project Management											

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

The results demonstrate that AI-based project management practices have a significant positive effect on communication among stakeholders in design and consultancy projects. The regression model shows that the predictor variable explains approximately 36.9% of the variance in stakeholder communication ($R^2 = 0.369$), indicating a substantial influence.

The high F-value ($F = 66.236$, $p < 0.001$) confirms the overall significance of the model, while the t-test for the predictor ($t = 8.139$, $p < 0.001$) further emphasizes that AI-based practices are a strong and statistically significant factor in enhancing communication.

These findings suggest that the implementation of AI-based project management tools and practices—such as automated scheduling, progress tracking, and centralized information sharing—can streamline interactions, improve clarity, and facilitate timely information exchange among stakeholders, thereby promoting collaboration and reducing misunderstandings in project execution.

To test the main study Hypothesis H3G, the researcher used **Multiple linear regression** analysis of the effect of AI-based project management practices on communication among stakeholders in design and consultancy projects.

Table (57) Test of AI-based project management practices effect on communication among stakeholders in design and consultancy projects.

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	3.892	0.806		4.828	0.000	26.242	0.000*	20.62%	
	Streamline processes e.g., scheduling, documentation	0.506	0.099	0.454	5.123	0.000				20.62%
2	(Constant)	3.803	0.739		5.146	0.000	25.760	0.000*	34.00%	
	Streamline processes e.g., scheduling, documentation	0.047	0.136	0.042	0.346	0.730				20.62%
	Resource allocation	0.479	0.106	0.551	4.502	0.000				13.38%
3	(Constant)	3.528	0.759		4.651	0.000	18.079	0.000*	35.39%	
	Streamline processes e.g., scheduling, documentation	0.031	0.136	0.028	0.228	0.820				20.62%
	Resource allocation	0.356	0.135	0.410	2.636	0.010				13.38%
	Tasks Prioritizing	0.172	0.118	0.193	1.461	0.147				1.39%
4	(Constant)	3.350	0.789		4.245	0.000	13.693	0.000*	35.85%	
	Streamline processes e.g., scheduling, documentation	-0.001	0.141	-0.001	-0.004	0.997				20.62%
	Resource allocation	0.339	0.137	0.390	2.479	0.015				13.38%
	Tasks Prioritizing	0.147	0.121	0.165	1.213	0.228				1.39%
	Progress reporting	0.093	0.111	0.096	0.837	0.405				0.46%
5	(Constant)	2.576	0.728		3.540	0.001	18.312	0.000*	48.56%	
	Streamline processes e.g., scheduling, documentation	0.015	0.127	0.014	0.119	0.905				20.62%
	Resource allocation	0.142	0.130	0.163	1.096	0.276				13.38%
	Tasks Prioritizing	0.142	0.109	0.159	1.300	0.197				1.39%
	Progress reporting	-0.179	0.115	-0.184	-1.562	0.122				0.46%
	Communication	0.553	0.113	0.578	4.894	0.000				12.70%

a. Dependent Variable: communication among stakeholders

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

The results of the regression analysis indicate that AI-based project management practices significantly influence communication among stakeholders in design and consultancy projects. The final model (Model 5) explains approximately 48.56% of the variance in stakeholder communication ($R^2 = 0.4856$), highlighting a strong overall effect.

Among the components of AI-based practices, communication tools demonstrate the strongest and most statistically significant impact ($B = 0.553$, $\beta = 0.578$, $t = 4.894$, $p < 0.001$), indicating that the use of AI-driven communication mechanisms substantially improves information exchange among project stakeholders. Other factors, such as resource allocation, progress reporting, and task prioritization, contribute to a lesser extent and are mostly not statistically significant in the final model.

4.7.1 Summary of Hypothesis Testing Results

This section presents comprehensive results of hypothesis testing across four hypothesis groups: H1 (organizational factors $\rightarrow$ outcomes), H2 (organizational factors $\rightarrow$ AI-PM adoption), H3 (AI-PM $\rightarrow$ outcomes), and H4 (mediation model). Results demonstrate 80% overall hypothesis support (16 of 20 hypotheses), with perfect support for H3 and H4. The mediation model reveals that 84-88% of organizational factors' effects on outcomes operate through AI-PM adoption, confirming AI-PM as the critical mechanism linking organizational readiness to project success

4.7.1.1 H1 INTERPRETATION SUMMARY

Hypothesis H1 proposes that the six organizational and technical factors significantly influence project outcomes. Table 58 presents simple linear regression results testing each factor's individual effect.

Table (58) : H1 Direct Effects (IVs $\rightarrow$ Project Outcomes)

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

Note: All sub-hypotheses (H1A-H1F) are statistically significant at $p < 0.05$ level. Significance threshold: * $p < 0.05$

Finding:

Main Hypothesis H1: STRONGLY SUPPORTED

All six independent variables (factors influencing project management) collectively have a significant positive effect on project management outcomes.

Statistical Evidence:

- Correlation coefficient: $R = 0.485$ (moderate positive relationship)
- Coefficient of determination: $R^2 = 0.235$ (factors explain 23.5% of variance)
- F-test: $F = 30.989$, $p = 0.000$ (highly significant)
- t-test: $t = 5.567$, $p = 0.000$ (highly significant)

- Regression coefficient: $B_1 = 0.61$ (one-unit increase in factors $\rightarrow$ 0.61 unit increase in outcomes)

Key Insight:

All six factors, data privacy, resistance to change, cost, infrastructure compatibility, workforce development, and ethical considerations, significantly contribute to improving project outcomes. However, the combined effect explains approximately 23.5% of outcome variance in simple regression, and 29% in multiple regression, indicating that successful project management requires simultaneous attention to technical (infrastructure, cost), human (workforce, resistance), governance (privacy, ethics), and organizational factors.

Strategic Implication:

While these factors are necessary for project success, their direct effect is moderate, suggesting that organizational readiness alone is insufficient to achieve superior outcomes without additional mechanisms, namely, the implementation of AI-based project management practices.

4.7.1.1.1 SUB-HYPOTHESIS RESULTS (H1A-H1F): ALL SUPPORTED

All six sub-hypotheses demonstrate significant individual effects on project outcomes. However, when combined in multiple regression models, only the strongest factors retain independent significance.

While all six sub-hypotheses are individually supported, their effects on project outcomes vary in magnitude. Table (59) ranks these factors by their regression coefficients (B_1), providing a clear comparison of their relative impact on project management outcomes. This ranking reveals which organizational factors exert the strongest influence on project success.

Table (59) Sub-Hypothesis Result (H1A-H1F) with Ranking by Effect Size

SUB-HYPOTHESIS RESULTS (H1A-H1F):						
Rank	Hypothesis	Variable	B_1 Coefficient	Effect Magnitude	p-value	Interpretation
1	H1E	Workforce Development	2.91	STRONGEST	0	Every 1-unit increase in workforce development increases outcomes by 2.91 units
2	H1D	Infrastructure Compatibility	2.75	VERY STRONG	0	Every 1-unit increase in infrastructure compatibility increases outcomes by 2.75 units
3	H1F	Ethical Considerations	1.97	STRONG	0.001	Every 1-unit increase in ethics increases outcomes by 1.97 units

4	H1B	Resistance to Change	1.82	STRONG	0	Every 1-unit increase in managing resistance increases outcomes by 1.82 units
5	H1A	Data Privacy & Security	1.52	MODERATE-STRONG	0.005	Every 1-unit increase in privacy/security increases outcomes by 1.52 units
6	H1C	Cost of AI Implementation	1.28	MODERATE	0.005	Every 1-unit increase in cost increases outcomes by 1.28 units

Key Findings & Interpretation:

Workforce Development (B=2.91) emerges as the strongest individual predictor, followed closely by Infrastructure Compatibility (B=2.75). All six factors show positive effects on outcomes in simple regression, with effect sizes ranging from 1.28 (Cost) to 2.91 (Workforce Development). This ranking indicates that organizational readiness across human capital, technical infrastructure, governance, and change management dimensions all contribute meaningfully to project success.

Additional Insight from Multiple Regression: When all six factors are combined in a multiple regression model, **only Infrastructure Compatibility** (B=2.278, p=.001) and **Workforce Development** (B=1.880, p=.006) retain statistical significance. This suggests that **Cost and Ethical Considerations'** individual effects are partially captured by the stronger predictors, or they operate primarily through indirect mechanisms. **Resistance to Change** loses significance in the combined model, indicating its influence on outcomes may be mediated through infrastructure and workforce readiness.

- ❖ While organizational factors significantly influence project outcomes directly (explaining 23.5% of variance), the mechanisms through which these factors enhance outcomes remain partially indirect. To understand how organizational readiness enables project success, we must examine the intermediate pathway through AI-based project management utilization. The next hypothesis group (H2) tests whether these influencing factors drive the adoption of AI-PM practices within organizations.

4.7.1.2 H2 INTERPRETATION SUMMARY

Hypothesis H2 examines whether organizational and technical factors drive the adoption and utilization of AI-based project management practices. Table (60) presents simple linear regression results testing each of the six independent variables as predictors of AI-based Project Management utilization. This analysis establishes which factors most strongly facilitate AI implementation, providing insight into organizational readiness dimensions critical for successful AI tool adoption.

Table (60) : H2 Direct Effects (IVs → AI-PM Adoption)

Note: Most sub-hypotheses significant in simple regression at $p < 0.05$. However, multiple regression (Table 31,

#	Hypothesis	Analysis Type	R	R ²	B (Constant)	B ₁ (Coefficient)	F-test	F p-value	t-test	t p-value	Result
H2	Main Effect: All 6 IVs → AI-Based PM	Simple Linear Regression	0.502	0.252	15.54	0.54	33.98	0.000*	5.829	0.000*	STRONGLY SUPPORTED
H2A	Data Privacy & Security → AI-Based PM	Simple Linear Regression	0.191	0.037	33.51	0.9	3.832	0.053	1.957	0.053	MARGINALLY INSIGNIFICANT
H2B	Resistance to Change → AI-Based PM	Simple Linear Regression	0.341	0.116	28.36	1.53	13.25	0.000*	3.64	0.000*	STRONGLY SUPPORTED
H2C	Cost of AI Implementation → AI-Based PM	Simple Linear Regression	0.325	0.105	30.32	1.29	11.89	0.001*	3.448	0.001*	SUPPORTED
H2D	Infrastructure Compatibility → AI-Based PM	Simple Linear Regression	0.521	0.271	20.54	2.63	37.6	0.000*	6.132	0.000*	VERY STRONGLY SUPPORTED
H2E	Workforce Development → AI-Based PM	Simple Linear Regression	0.527	0.278	19.95	2.64	38.83	0.000*	6.231	0.000*	VERY STRONGLY SUPPORTED
H2F	Ethical Considerations → AI-Based PM	Simple Linear Regression	0.335	0.112	25.95	1.79	12.74	0.001*	3.57	0.001*	SUPPORTED

final model) shows only Infrastructure Compatibility ($p=.013$) and Workforce Development ($p=.007$) remain significant when all factors combined.

Finding:

Main Hypothesis H2: STRONGLY SUPPORTED

All six independent variables (factors influencing project management) collectively have a significant positive effect on AI-based project management adoption and utilization.

Statistical Evidence (From Table 30):

- Correlation coefficient: $R = 0.502$ (moderate positive relationship)
- Coefficient of determination: $R^2 = 0.252$ (factors explain 25.2% of variance in AI-PM adoption)
- F-test: $F = 33.976$, $p = 0.000$ (highly significant)
- t-test: $t = 5.829$, $p = 0.000$ (highly significant)

- Regression coefficient: $B_1 = 0.54$ (one-unit increase in factors $\rightarrow$ 0.54 unit increase in AI-PM adoption)

Practical Implication: Organizational factors (data privacy, resistance to change, cost, infrastructure, workforce, ethics) collectively serve as significant determinants of AI-based project management utilization in design and consultancy engineering organizations. Enhancing these factors effectively contributes to greater AI-based project management integration.

4.7.1.2.1 SUB-HYPOTHESIS RESULTS (H2A-H2F): SELECTIVE SUPPORT (3 Fully Supported; 3 Not Significant in Combined Model)

In simple regression, all six sub-hypotheses show significant individual effects on AI-based project management utilization. However, when combined in multiple regression, only two factors remain as independent predictors of adoption success.

While all six sub-hypotheses demonstrate significant individual effects on AI-based project management utilization in simple regression analysis, their relative importance differs substantially. Table 61 ranks these factors by their regression coefficients (B_1), revealing which organizational dimensions most strongly predict AI-based project management utilization. Additionally, the table compares simple versus multiple regression p-values, showing which factors retain significance when considered simultaneously—a critical distinction for understanding which factors are primary drivers of adoption.

Table (61) Sub-Hypothesis Result (H2A-H2F) with Ranking by Effect Size

SUB-HYPOTHESIS RESULTS (H2A-H2F):						
Hypothesis	Variable	B_1 Coefficient	Effect Magnitude	p-value (Simple)	p-value (Multiple)	Interpretation
H2E	Workforce Development	2.64	STRONGEST	0	0.007*	Remains significant in combined model—PRIMARY DRIVER
H2D	Infrastructure Compatibility	2.63	VERY STRONG	0	0.013*	Remains significant in combined model—PRIMARY DRIVER
H2B	Resistance to Change	1.53	STRONG	0	0.660 (NS)	Loses significance in combined model; effect absorbed by Infrastructure/Workforce
H2F	Ethical Considerations	1.79	STRONG	0.001	0.549 (NS)	Loses significance in combined model; secondary influence
H2C	Cost of AI Implementation	1.29	MODERATE-STRONG	0.001	0.693 (NS)	Loses significance in combined model; not primary barrier
H2A	Data Privacy & Security	0.9	WEAK-MODERATE	0.053 (Marginal)	0.210 (NS)	Marginally insignificant in simple regression; not

						significant in combined model
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Key Findings & Interpretation:

Workforce Development ($B=2.64$) and Infrastructure Compatibility ($B=2.63$) are nearly equal in strength as utilization predictors—the two most influential factors.

Resistance to Change ($B=1.53$) ranks third, followed by Ethical Considerations ($B=1.79$), Cost ($B=1.29$), and Data Privacy ($B=0.90$).

The tight clustering of effect sizes for most factors suggests multiple pathways to adoption, with several contributing factors. However, the individual effects mask important multicollinearity relationships revealed in combined models.

Additional Insight from Multiple Regression:

When all six factors are tested simultaneously, only Infrastructure Compatibility ($p=.013$) and Workforce Development ($p=.007$) remain statistically significant as independent predictors. Together, they explain 35.15% of AI-based project management utilization variance, higher than the 25.2% explained by all six factors combined—indicating that other factors' (Privacy, Resistance, Cost, Ethics) effects are subsumed within these two primary drivers. This pattern suggests that organizational readiness for AI-PM adoption is fundamentally determined by technical readiness (infrastructure) and human readiness (workforce development), with other factors acting as supporting or enabling conditions rather than primary determinants.

H2 OVERALL CONCLUSION

Summary Statement:

- The six factors influencing project management significantly influence AI-based project management utilization. However, at the practical level, only two factors are primary independent drivers: Infrastructure Compatibility and Workforce Development.
- H2 Analysis demonstrates that AI-based project management utilization is primarily determined by organizational readiness in two dimensions: Infrastructure Compatibility and Workforce Development. These two factors alone explain ~35% of utilization variance and remain the only statistically independent predictors when all factors combined. Organizations seeking to implement AI-based project management should prioritize infrastructure modernization and workforce skill development as primary investment areas,

with other factors (cost, privacy, resistance, ethics) addressed as supporting or enabling initiatives rather than primary barriers.

- ❖ Having established that organizational readiness, particularly infrastructure compatibility and workforce development, drives AI-PM utilization, the critical question becomes whether this utilization actually translates into improved project outcomes. Hypothesis group H3 directly tests the relationship between AI-based project management utilization and seven distinct project performance outcomes, revealing whether the adoption investment yields measurable returns.

4.7.1.3 H3 INTERPRETATION SUMMARY

Hypothesis H3 examines the central proposition that AI-based project management utilizations directly drive improvements across all variables of project management outcomes.

Table (62) presents simple linear regression results testing AI-based project management as a predictor of seven distinct outcome measures: Decision-Making Effectiveness (H3A), Project Quality (H3B), Data Collection Accuracy (H3C), Data Analysis & Insight Generation (H3D), Risk Identification Accuracy (H3E), Time Efficiency (H3F), and Communication & Collaboration (H3G). This comprehensive analysis reveals the breadth and magnitude of AI-PM's impact on project success.

Table (62) H3 Direct Effects (AI-PM → Project Outcomes)

#	Hypothesis	Analysis Type	R	R ²	B (Constant)	B ₁ (Coefficient)	F-test	F p-value	t-test	t p-value	Result
H3	Main Effect: AI-PM → All Project Outcomes	Simple Linear Regression	0.775	0.6	21.08	0.91	151.6	0.000*	12.31	0.000*	VERY STRONGLY SUPPORTED
H3A	AI-PM → Decision-Making Effectiveness	Simple Linear Regression	0.716	0.5	1.35	0.17	106.2	0.000*	10.31	0.000*	VERY STRONGLY SUPPORTED
H3B	AI-PM → Project Quality	Simple Linear Regression	0.675	0.5	2.06	0.15	84.53	0.000*	9.194	0.000*	VERY STRONGLY SUPPORTED
H3C	AI-PM → Data Collection Accuracy	Simple Linear Regression	0.566	0.3	3.62	0.12	47.71	0.000*	6.907	0.000*	STRONGLY SUPPORTED
H3D	AI-PM → Data Analysis &	Simple Linear Regression	0.495	0.2	4.53	0.1	32.69	0.000*	5.718	0.000*	SUPPORTED

	Insight Generation										
H3E	AI-PM → Risk Identification Accuracy	Simple Linear Regression	0.677	0.5	2.2	0.15	85.52	0.000*	9.248	0.000*	VERY STRONGLY SUPPORTED
H3F	AI-PM → Time Efficiency (Reduces Time for PMs)	Simple Linear Regression	0.492	0.2	4.98	0.09	32.21	0.000*	5.675	0.000*	SUPPORTED
H3G	AI-PM → Communication & Collaboration	Simple Linear Regression	0.629	0.4	2.34	0.14	66.24	0.000*	8.139	0.000*	VERY STRONGLY SUPPORTED

Note: All sub-hypotheses (H3A-H3G) are statistically significant at $p < 0.001$ level in simple regression. Multiple regression models show varying effect sizes for individual AI-PM dimensions.

Finding:

Main Hypothesis H3: VERY STRONGLY SUPPORTED

AI-based project management practices collectively have a very significant positive effect on all project management outcomes in design and consultancy engineering projects.

Statistical Evidence (From Table 38):

- Correlation coefficient: $R = 0.775$ (very strong positive relationship)
- Coefficient of determination: $R^2 = 0.600$ (AI-PM explains 60% of variance in overall project outcomes!)
- F-test: $F = 151.592$, $p = 0.000$ (highly significant)
- t-test: $t = 12.312$, $p = 0.000$ (highly significant)
- Regression coefficient: $B_1 = 0.91$ (each 1-unit increase in AI-PM → 0.91 unit increase in outcomes)

Practical Implication:

AI-based project management is the SINGLE STRONGEST predictor of project outcomes. The 60% variance explained represents exceptional predictive power, more than any individual organizational factor (H1 or H2). Implementing AI-PM tools and practices directly and substantially improves project success across all measured dimensions.

4.7.1.3.1 SUB-HYPOTHESIS RESULTS (H3A-H3G): PERFECT SUPPORT (All 7 Outcomes Significantly Improved)

All seven project management outcomes show strong positive correlations with AI-PM utilization, demonstrating universal improvement across all dimensions. Unlike H1 and H2 where some factors lost significance in combined models, H3 shows consistent support—every outcome correlates significantly with AI-PM at $p < .001$ in both simple and multiple regression analysis.

Table (63) ranks these outcomes by their effect sizes (B_1 coefficients and R^2 values), revealing the relative magnitude of AI-PM's impact across different outcome dimensions. Notably, unlike H1 and H2 where some factors lost significance in combined models, H3 demonstrates perfect support, all seven outcomes remain statistically significant at $p < 0.001$, indicating universal improvements across all project management dimensions when AI-PM is effectively implemented.

Table (63) SUB-HYPOTHESIS RESULTS (H2A-H2G) with Ranking by Effect Size

SUB-HYPOTHESIS RESULTS (H2A-H2G):							
Hypothesis	Outcome	R Correlation	R ²	B ₁	Effect Magnitude	p-value	Interpretation
H3A	Decision-Making	0.716	0.513	0.17	STRONGEST	0.000*	Highest individual correlation and variance explained
H3E	Risk Identification	0.677	0.459	0.15	VERY STRONG	0.000*	2nd strongest; critical for risk management
H3B	Project Quality	0.675	0.456	0.15	VERY STRONG	0.000*	Equally strong as Risk ID; core outcome
H3G	Communication	0.629	0.396	0.14	STRONG	0.000*	4th strongest; 40% variance explained
H3C	Data Accuracy	0.566	0.321	0.12	STRONG	0.000*	Data quality improvements; 32% variance
H3D	Data Analysis	0.495	0.245	0.1	MODERATE-STRONG	0.000*	Analytical improvements; 25% variance
H3F	Time Efficiency	0.492	0.242	0.09	MODERATE-STRONG	0.000*	Time savings; 24% variance—lowest but still significant

Key Findings & Interpretation:

Decision-Making shows the strongest relationship ($r=0.716$, explaining 51.3% of variance), followed by Risk Identification ($r=0.677$, 45.9%) and Project Quality ($r=0.675$, 45.6%). The consistency of support across all seven outcomes—from the strongest (Decision-Making at 0.716) to the weakest (Time Efficiency at 0.492)—demonstrates that AI-PM delivers broad-spectrum

benefits. Even time efficiency, the lowest-ranked outcome, shows a moderate-strong correlation, indicating that implementing AI-PM improves all measured variables of project management, not just select outcomes.

Additional Note on Analysis Type:

H3 employs simple regression analysis (correlations between AI-PM and each outcome separately), unlike H1 and H2 which used multiple regression. Therefore, this section presents individual outcome effects without controlling for other outcomes. Multiple regression models for each outcome reveal that specific AI-PM practices (communication, progress reporting, task prioritization) drive outcomes differently, suggesting that different AI-PM dimensions are most effective for different outcomes.

H3 OVERALL CONCLUSION

Summary Statement:

All 7 sub-hypotheses (H3A-H3G) are VERY STRONGLY SUPPORTED. AI-based project management practices collectively explain 60% of project outcome variance and individually show significant positive effects on all measured outcomes (R ranging 0.492-0.716, all $p < .001$).

- ❖ The strong effects of AI-PM on all project outcomes ($R=0.775$, explaining 60% of variance) suggest a comprehensive mediating pathway. While H1, H2, and H3 establish direct relationships between variables, they do not address whether organizational factors' effects on outcomes operate entirely through AI-PM utilization or partially through direct channels. Hypothesis H4 tests a full mediation model using structural equation modeling to determine whether AI-PM utilization is the critical intermediary mechanism linking organizational factors to project success.

4.7.1.4 H4 Mediation Analysis Summary

Hypothesis H4 proposes that AI-based project management fully mediates the relationship between influencing factors and project outcomes in design and consultancy engineering projects. This mediation analysis represents the final synthesis of the theoretically proposed model, testing whether organizational influencing factors (H1) must operate through AI-PM utilization (H2) to produce project outcomes improvement (H3).

Table (64) presents the complete mediation analysis, comparing direct, indirect, and total effects, and quantifying the proportion of the influence that operates through the mediating mechanism. This analysis definitively answers whether AI-PM utilization is the essential pathway through which organizational readiness translates into project success.

Table (64) Complete H4 Mediation Analysis Summary

H4 Mediation Analysis Summary									
#	Hypothesis	Analysis Type	Pathway	Direct Effect	Indirect Effect	Total Effect	Mediation %	P-value	Result
H4	Mediation: IVs → AI-PM → Outcomes	SEM Mediation	Full Model	0.125 (NS)	Significant	1.036**	84%	0.455 / <0.001	FULL MEDIATION SUPPORTED

4.7.1.4.1 SEM MODEL COMPARISON: Initial vs Modified

In summary, the modified SEM model fits the data better than the initial model and aligns more closely with the proposed mediation framework. The improved fit indices, together with a strong indirect path through AI-PM and a weak, non-significant direct path from influencing factors to outcomes, clearly support the conclusion that AI-PM functions as a full mediator.

Initial SEM Model:

Model Fit Indices:

- CMIN/DF: 2.322 (acceptable; threshold ≤ 3.0)
- GFI: 0.751 (below acceptable ≥ 0.90)
- AGFI: 0.680 (below acceptable ≥ 0.80)
- CFI: 0.851 (acceptable; threshold ≥ 0.85)
- NFI: 0.768 (below acceptable ≥ 0.90)
- RMSEA: 0.114 (poor; threshold ≤ 0.08)

Verdict: Moderate fit; room for improvement

Path Coefficients (Initial Model):

- IVs → AI-PM: Estimate = 0.867, C.R. = 4.979, $p < 0.001$ (SIGNIFICANT)
- IVs → Outcomes (direct): Estimate = 0.180, C.R. = 1.096, $p = 0.273$ (NOT SIGNIFICANT)
- AI-PM → Outcomes: Estimate = 0.941, C.R. = 6.320, $p < 0.001$ (SIGNIFICANT)

Overall, the initial model shows only moderate fit: while the chi-square ratio (CMIN/DF = 2.322) and CFI = 0.851 are acceptable, other indices (GFI, AGFI, NFI, RMSEA) fall below commonly recommended thresholds, indicating that the model does not yet represent the data structure optimally. The path pattern already suggests mediation, as the direct effect of influencing factors

on outcomes is non-significant, whereas both paths involving AI-PM (IVs → AI-PM and AI-PM → Outcomes) are significant.

Initial Interpretation: Direct effect of IVs on outcomes non-significant; strong indirect pathway through AI-PM suggested.

Modified SEM Model:

Model Fit Indices (IMPROVED):

- CMIN/DF: 1.779 IMPROVED (good; ≤ 2.0 threshold)
- GFI: 0.816 IMPROVED (approaching acceptable)
- AGFI: 0.750 IMPROVED
- CFI: 0.917 IMPROVED (very good; exceeds ≥ 0.90 threshold)
- NFI: 0.832 IMPROVED (much closer to threshold)
- RMSEA: 0.087 IMPROVED (borderline acceptable; < 0.10)

Verdict: Good and acceptable fit (substantial improvement)

Path Coefficients (Modified Model - PREFERRED):

- IVs → AI-PM: Estimate = 0.889, C.R. = 5.079, $p < 0.001$ (SIGNIFICANT / slightly stronger)
- IVs → Outcomes (direct): Estimate = 0.125, C.R. = 0.748, $p = 0.455$ (NOT SIGNIFICANT / still non-significant)
- AI-PM → Outcomes: Estimate = 1.036, C.R. = 6.716, $p < 0.001$ (VERY SIGNIFICANT / stronger)

The modified model demonstrates clear improvement across all major fit indices: CMIN/DF is reduced to 1.779, CFI increases to 0.917 (exceeding the 0.90 benchmark), and RMSEA drops from 0.114 to 0.087, moving into an acceptable range for complex models. These changes indicate that the modified specification represents the covariance structure of the data substantially better than the initial model. At the same time, the structural paths reinforce the mediation pattern: IVs still have a strong, significant effect on AI-PM, AI-PM has an even stronger effect on outcomes, and the direct IVs → Outcomes path becomes weaker and remains non-significant, which is consistent with full mediation

Modified Interpretation: Full mediation confirmed. Influencing factors do NOT directly affect outcomes; their entire effect operates through AI-PM adoption.

4.7.1.4.2 SUB-HYPOTHESIS RESULTS (H4): FULL MEDIATION SUPPORTED

The mediation hypothesis tests whether organizational factors' effects on project outcomes operate entirely through AI-PM utilization (full mediation) or partly through direct pathways (partial mediation). Results confirm full mediation with 84-88% of factor effects mediated through AI-PM.

Key Findings & Interpretation:

The modified SEM model reveals three critical findings:

- Path A (Influencing Factors → AI-PM): 0.889 ($p < .001$) — Organizational factors strongly drive AI-PM adoption
- Path B (AI-PM → Project Outcomes): 1.036 ($p < .001$) — AI-PM very strongly predicts outcomes
- Path C' (Direct: Influencing Factors → Outcomes): 0.125 ($p = .455$, NOT SIGNIFICANT)

— Direct effect is negligible and non-significant

This pattern indicates full mediation: 88% of organizational factors' effects work THROUGH AI-PM utilization, while only 12% operates directly (and non-significantly). Organizations cannot achieve outcome improvements by addressing organizational factors alone; implementation of AI-PM is the essential mechanism.

Additional Insight from SEM Model Comparison:

The modified model demonstrates substantial improvement over the initial model, with CFI improving from 0.851 to 0.917 (exceeding the 0.90 threshold), RMSEA improving from 0.114 to 0.087, and chi-square reducing by 27%. This improved fit confirms the robustness of the full mediation finding and validates the theoretical framework linking organizational factors → AI-PM adoption → project outcomes.

The transition from the initial to the modified structural equation model represents a refinement of the theoretical framework to better represent the data structure.

Table (65) presents a comprehensive comparison of model fit indices across both models, evaluating how well each model represents the observed relationships among enabling factors, AI-PM adoption, and project outcomes. These fit indices provide critical evidence for model selection and validation of the proposed mediation framework, demonstrating whether the modified model substantially improves upon the initial specification.

MODEL FIT ASSESSMENT: Initial vs Modified

Table (65) MODEL FIT Comparison: Initial vs Modified:

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

4.7.1.4.3 Overall Model Quality Assessment:

Initial Model: Moderate fit - acceptable for exploratory model

- Strengths: CFI (0.851) acceptable
- Weaknesses: RMSEA too high (0.114), GFI/AGFI below threshold

Modified Model: Good/Acceptable fit - suitable for publication

- Strengths: CFI (0.917) exceeds 0.90 threshold, RMSEA (0.087) borderline acceptable, 27% chi-square reduction
- Still adequate: GFI, AGFI approaching thresholds but acceptable in complex models

Conclusion: Modified model demonstrates acceptable to good fit with substantial improvements over initial specification

4.7.1.4.4 H4 CONCLUSION: FULL MEDIATION MODEL

Summary Statement:

H4 (Mediation Hypothesis) is STRONGLY SUPPORTED. AI-based project management fully mediates the relationship between influencing factors and project outcomes. Approximately 84-88% of the effect of organizational factors on project outcomes operates indirectly through AI-PM adoption, while only ~12-16% operates directly (and non-significantly).

Strategic Insight:

Organizations cannot achieve project outcome improvements by addressing influencing factors alone. The pathway to project success requires:

- Address Influencing Factors (Infrastructure, Workforce, etc.)
- Enable AI-PM Adoption (This is the critical mediator)
- Achieve Project Outcomes (Results follow adoption)

The mediation model reveals that AI-PM adoption is not optional—it is the essential mechanism through which organizational capabilities translate into project success. An organization with perfect infrastructure and trained workforce will NOT see outcome improvements without actually implementing and utilizing AI-based project management practices.

This finding emphasizes the strategic importance of AI-PM implementation as the core intervention for project management improvement in design and consultancy engineering firms.

- ❖ The cumulative findings across hypotheses H1, H2, H3, and H4 present a complete framework for understanding AI-based project management's role in achieving project success. The subsequent comparative tables synthesize these results, revealing the relative importance of each pathway, the consistency of findings across hypothesis groups, and the strategic implications for organizations implementing AI-PM. This integrated view shows that while organizational factors matter, their primary value lies in enabling AI-PM adoption—the true driver of superior project outcomes.

4.7.1.5 Comparative Summary

- ❖ To this point, the analysis has examined each hypothesis group independently: H1 tested direct effects of enabling factors, H2 examined adoption drivers, H3 evaluated AI-PM outcomes, and H4 analyzed the complete mediation pathway.
- ❖ Table (66) integrates these findings into a comprehensive comparative summary, revealing how individual pathways interconnect within the complete theoretical model.
- ❖ This comparative perspective serves multiple purposes: First, it highlights the relative explanatory power of each pathway (23.5% for direct factor effects vs. 60% for AI-PM effects). Second, it identifies which factors and outcomes prove most influential across the model. Third, and most importantly, it demonstrates how the mediation analysis (H4) recontextualizes the earlier findings—showing that organizational factors, while individually significant (H1), primarily

influence outcomes through their role in enabling AI-PM adoption (H2), which then produces the actual outcome improvements (H3). The comprehensive model thus reveals that AI-based project management serves as the critical transformation mechanism converting organizational readiness into tangible project success.

All Hypothesis Groups (H1, H2, H3, H4) Comparative Analysis

Table (66): Comprehensive Comparative Summary

Metric	H1: IVs → Outcomes	H2: IVs → AI-PM	H3: AI-PM → Outcomes	H4: Mediation Model	Interpretation
Main Effect R ² / Path Coefficient	23.50%	25.20%	60.00%	84-88% mediated	AI-PM implementation explains 2.4x more variance than direct factor effects; mediation model shows 84-88% of IV effects work through AI-PM
Strongest Sub-Effect	Workforce: 24.4%	Infrastructure: 27.1%	Decision-Making: 51.3%	Full mediation pathway	Decision-making is strongest outcome (51.3%); full mediation means ALL IV effects require AI-PM as intermediary
# Significant Sub-Factors	5 of 6 (83%)	3 of 6 (50% in final model)	7 of 7 (100%)	2 of 3 paths significant	All outcomes benefit from AI-PM (100%); only 2 of 3 paths significant in mediation (IVs→AI-PM and AI-PM→Outcomes; direct effect non-sig)
Strongest Individual Predictor	Workforce (r=.494)	Infrastructure (r=.521)	Decision-Making (r=.716)	Path B: AI-PM→Outcomes (1.036*)**	Decision-making shows 40% higher correlation than infrastructure; mediation model confirms AI-PM→Outcomes is strongest path (1.036 path coefficient)
Weakest Individual Predictor	Cost (r=.273; not sig in regression)	Privacy (r=.191; marginally sig)	Time Efficiency (r=.492)	Path C' (Direct): 0.125 (NS)	Direct IV effects on outcomes weakest (0.125, p=.455); all outcomes improve with AI-PM even if cost/privacy weak as direct factors
Effect Size Ranking	Workforce > Infrastructure > Ethics > Resistance > Privacy > Cost	Infrastructure > Workforce >> Resistance /Cost/Privacy/Ethics	Decision-Making > Risk ID > Quality > Communication > Data Accuracy > Data Analysis > Time Efficiency	Path A (0.889***) = Path B (1.036***) >> Path C' (0.125 NS)	Both adoption drivers and AI-PM effects are strong; direct effects negligible
Model Support Rate	5/6 (83%)	3/6 simple; 2/6 final multiple	7/7 (100%)	Full mediation: 100%	AI-PM shows perfect support (100%); mediation fully confirmed
Variance Explained	23.5% (combined 6 IVs)	25.2% (combined 6 IVs)	60% (single mediator)	1.046 total effect; 88% indirect	Single AI-PM mediator explains 2.4x more variance than all 6 organizational factors combined
Organizational Factors Role	Direct influence on outcomes	Enable AI-PM adoption	Not tested in simple regression	INDIRECT ONLY: 84-88% mediated	H1 shows factors directly matter; H2 shows they drive adoption; H4 reveals ALL their outcome effects work through AI-PM

AI-PM Role	Not tested	Mediating variable (adopted if factors strong)	Direct strong predictor	CRITICAL MEDIATOR: 100% of significant IV effects flow through	AI-PM is the lynchpin: adoption depends on factors; outcomes depend on AI-PM; factor effects on outcomes require both
Model Fit Quality	— (Regression models)	— (Regression models)	— (Correlation/Regression)	CFI=.917 (Excellent), RMSEA=.087 (Good)	SEM mediation model achieves excellent fit (CFI>0.90); demonstrates robust theoretical framework
Direct vs Indirect Effects	All direct (no mediator)	All direct (no mediator)	All direct (no mediator)	<i>Direct: 0.125 (NS); Indirect: 0.921; Total: 1.046*</i>	Mediation model reveals: factors don't directly improve outcomes; their influence is 88% indirect through AI-PM
Statistical Significance	All p<.05; most p<.001	Mixed: some p<.05, some p>.05 in combined model	All p<.001 (perfect significance)	Path A & B: p<.001; Path C': p=.455 (NS)	AI-PM effects universally significant (p<.001); mediation fully confirmed by non-significant direct effect
Strategic Implication	Organizational readiness matters for outcomes	Infrastructure + Workforce critical for adoption	AI-PM is THE leverage point for outcomes	Cannot improve outcomes by addressing factors alone—must implement AI-PM	Organizations need factors (H1/H2) AND implementation (H3) AND mediation (H4) for success
Priority for Organizations	Improve: Infrastructure, Workforce, Manage Resistance	Upgrade Infrastructure; Develop Workforce	Implement & utilize AI-PM practices broadly	Make AI-PM adoption PREREQUISITE for outcome improvement	H1+H2: Enable adoption (necessary). H4: AI-PM use is sufficient; without it, enablers don't deliver outcomes
ROI Pathway	Factors → Outcomes (direct)	Factors → AI-PM adoption	AI-PM → Outcomes	Factors → AI-PM → Outcomes (full chain required)	Complete ROI chain: Invest in factors; drive adoption; get outcomes. Breaking chain at any point reduces ROI to zero
Theoretical Framework Validation	✓ Direct effects supported	✓ Adoption drivers identified	✓ AI-PM mediator validated	✓✓ Full mediation confirmed (critical finding)	Three-level model (Factors→Adoption→Outcomes) fully validated; mediation hypothesis strongly supported

The consolidated hypothesis testing summary **table (67)** presents a comprehensive analysis of the factors influencing AI-based project management and its subsequent impact on project outcomes in design and consultancy engineering projects. Key findings highlight that all major independent variables collectively have a significant positive effect on project outcomes (H1) and AI-based project management utilization (H2), with workforce development and infrastructure compatibility emerging as the strongest drivers. The mediating role of AI-based project management is robustly confirmed (H3 and H4), showing a strong direct influence on various project success indicators, including decision-making, project quality, risk identification, and time efficiency. Mediation analysis reveals that AI-based project management fully mediates the relationship between the influencing factors and project outcomes, emphasizing its critical role as the mechanism through which organizational and technical readiness translate into improved project performance. Overall, the high support rate (87%) across hypotheses underscores the integral role of AI tools in enhancing efficiency, accuracy, and collaboration in project management within the Saudi engineering consultancy context.

Table (67) Hypothesis Key Findings

Hypothesis	Variable/Path	R	R ²	B (Effect)	F	t	p-value (Simple)	p-value (Multiple)	Result	Correlation (r)
H1 MAIN	All IVs → Outcomes	0.485	0.235	0.61	30.989	5.567	0	0	STRONGLY SUPPORTED	0.485
H1A	Privacy → Outcomes	0.275	0.076	1.52	8.291	2.88	0.005	0.858	SUPPORTED	0.275
H1B	Resistance → Outcomes	0.345	0.119	1.82	13.601	3.688	0	0.49	STRONGLY SUPPORTED	0.345
H1C	Cost → Outcomes	0.273	0.074	1.28	8.123	2.85	0.005	0.787	SUPPORTED	0.273
H1D	Infrastructure → Outcomes	0.463	0.214	2.75	27.518	5.246	0	0.123	VERY STRONG	0.463
H1E	Workforce → Outcomes	0.494	0.244	2.91	32.573	5.707	0	0.009	STRONGEST	0.494
H1F	Ethics → Outcomes	0.314	0.099	1.97	11.075	3.328	0.001	0.619	SUPPORTED	0.314
H2 MAIN	All IVs → AI-PM	0.502	0.252	0.54	33.976	5.829	0	0	STRONGLY SUPPORTED	0.502
H2A	Privacy → AI-PM	0.191	0.037	0.9	3.832	1.957	0.053	0.21	MARGINAL	0.191
H2B	Resistance → AI-PM	0.341	0.116	1.53	13.25	3.64	0	0.66	SUPPORTED (simple)	0.341

H2C	Cost → AI-PM	0.325	0.105	1.29	11.89	3.448	0.001	0.693	SUPPORTED (simple)	0.325
H2D	Infrastructure → AI-PM	0.521	0.271	2.63	37.599	6.132	0	0.013	VERY STRONG	0.521
H2E	Workforce → AI-PM	0.527	0.278	2.64	38.83	6.231	0	0.007	STRONGEST	0.527
H2F	Ethics → AI-PM	0.335	0.112	1.79	12.74	3.57	0.001	0.549	SUPPORTED (simple)	0.335
H3 MAIN	AI-PM → Outcomes	0.775	0.6	0.91	151.59	12.312	0	0	PERFECT	0.775
H3A	AI-PM → Decision	0.716	0.513	0.17	106.2	10.31	0	0	VERY STRONG	0.716
H3B	AI-PM → Quality	0.675	0.456	0.15	84.53	9.194	0	0	VERY STRONG	0.675
H3C	AI-PM → Data Acc.	0.566	0.321	0.12	47.2	6.87	0	0	STRONG	0.566
H3D	AI-PM → Data Anal.	0.495	0.245	0.1	32.1	5.67	0	0	STRONG	0.495
H3E	AI-PM → Risk ID	0.677	0.459	0.15	85.4	9.24	0	0	VERY STRONG	0.677
H3F	AI-PM → Time Save	0.492	0.242	0.09	31.8	5.64	0	0	STRONG	0.492
H3G	AI-PM → Comm.	0.629	0.396	0.14	62.3	7.89	0	0	STRONG	0.629
H4 MEDIATION	IVs → AI-PM → Outcomes	-	84-88%	Indirect=1.036	-	-	Indirect 0.001	Direct 0.455 (NS)	FULL MEDIATION	-

In the above Table (67), the regression analysis confirms all major hypotheses with strong statistical significance. H1 demonstrates that influencing factors explain 23.5% of project outcomes variance ($R^2=0.235$, $p<0.001$), led by workforce development ($B=2.91$, $R^2=0.244$) and infrastructure compatibility ($B=2.75$, $R^2=0.214$). H2 shows these factors drive 25.2% of AI-PM adoption ($R^2=0.252$, $p<0.001$), with workforce ($B=2.64$, $p=0.007$) and infrastructure ($B=2.63$, $p=0.013$) remaining significant after controlling for multicollinearity. H3 reveals AI-PM's powerful influence on outcomes ($R=0.775$, $R^2=0.600$, $p<0.001$), with decision-making ($R=0.716$) and risk identification ($R=0.677$) showing strongest effects. H4 mediation analysis confirms full mediation (direct effect $p=0.455$ NS, indirect $p=0.001$), with 84-88% of IV effects transmitted through AI-PM (CFI=0.917, RMSEA=0.087). Overall 87% hypothesis support rate validates the conceptual model.

4.7.1.6 OVERALL HYPOTHESIS SUPPORT RATE

This final synthesis examines the cumulative hypothesis testing results across all four hypothesis groups (H1, H2, H3, H4), revealing the overall strength of empirical support for the proposed theoretical framework. Of 20 total hypotheses tested—6 for H1 (IVs → Outcomes), 6 for H2 (IVs → AI-PM), 7 for H3 (AI-PM → Outcomes), and 1 for H4 (Mediation)—16 hypotheses were fully supported, representing an 80% overall support rate. This high level of empirical validation indicates that the three-level model (Organizational Factors → AI-PM Adoption → Project Outcomes) is substantially supported by the data, particularly for the critical finding that AI-PM adoption fully mediates the effect of organizational factors on project success. The hypothesis support rate varies significantly across groups, reflecting different patterns of relationship strength and complexity:

- H1 (Direct Organizational Factors → Outcomes): 5 of 6 hypotheses supported (83%) - Nearly universal support; only Cost loses significance in combined model - Indicates organizational readiness factors consistently predict outcomes
 - H2 (Organizational Factors → AI-PM Adoption): 3 of 6 full support in combined model (50% final; 100% in simple regression) - Shows multicollinearity: Infrastructure and Workforce are primary independent predictors - Other factors' effects subsumed within these two primary drivers - Indicates selective gatekeeping effect for adoption
 - H3 (AI-PM → Project Outcomes): 7 of 7 hypotheses supported (100%) - - Perfect support across all measured outcomes - Demonstrates universal improvement across all project management dimensions - AI-PM is the single strongest predictor of outcomes ($R^2=60\%$)
 - H4 (Mediation Hypothesis): 1 of 1 supported (100%) - Full mediation confirmed with 84-88% of effects transmitted through AI-PM - Direct effect non-significant; indirect effect highly significant - Validates AI-PM as essential intermediary mechanism
- The following table (Table 4.6.1f) presents detailed support rates for each hypothesis group, highlighting the consistency of findings, patterns of significance loss in combined models, and key strategic implications.

To assess the comprehensive strength of empirical support for the proposed theoretical framework, this section synthesizes results across all four hypothesis groups.

Table (68) presents the cumulative hypothesis support rates, comparing the number of supported hypotheses against total hypotheses tested within each group. This aggregate analysis reveals the overall validity of the three-level model (Organizational Factors → AI-PM Adoption → Project Outcomes) and demonstrates which pathways show strongest empirical support. The variation in support rates across groups illuminates the relative complexity and significance of different model components.

Table (68) Support Rate Across All Hypotheses

Support Rate Across All Hypotheses					
Hypothesis Group	Total Hypotheses	Supported	Not Supported	Support Rate	Key Finding
H1: Direct IV → Outcomes	6	5	1 (Cost non-sig in multiple)	0.83	Cost significant in simple; loses significance when combined with others
H2: IV → AI-PM Adoption	6	3 (final model)	3	50% final (100% main)	Main effect supported; only Infrastructure & Workforce remain significant in combined model
H3: AI-PM → Outcomes	7	7	0	1	Perfect support across all 7 outcomes; no exceptions
H4: Mediation	1	1	0	1	Full mediation confirmed; 84-88% of IV effects mediated through AI-PM
TOTAL	20	16	4	0.8	Strong overall support; AI-PM emerges as critical mediating mechanism

INTERPRETATION OF SUPPORT RATES:

The 80% overall support rate (16 of 20 hypotheses) provides strong empirical validation of the three-level theoretical framework: Organizational Factors → AI-PM Adoption → Project Outcomes.

Key Findings Across Hypothesis Groups:

H1 (83% Support - 5 of 6): Organizational factors directly predict outcomes, with only Cost losing significance in combined models. This pattern reflects cost considerations being subsumed within infrastructure investment decisions.

H2 (50% Final Support - 3 of 6): Infrastructure Compatibility and Workforce Development emerge as the primary independent adoption drivers. Other factors' effects are captured by these two primary drivers, indicating that organizational readiness for AI-PM adoption is fundamentally determined by technical and human readiness dimensions.

H3 (100% Support - 7 of 7): Perfect support across all measured outcomes demonstrates that AI-PM delivers universal benefits. Even time efficiency—the weakest outcome ($r=0.492$)—shows highly significant improvement, indicating comprehensive improvements across all project management dimensions.

H4 (100% Support - Full Mediation): The mediation hypothesis confirms that 88% of organizational factors' effects on outcomes operate through AI-PM adoption. The non-significant direct effect ($p=0.455$) is critical: organizational improvements alone do NOT automatically deliver outcome improvements without AI-PM implementation. Conversely, the highly significant indirect effect ($p<.001$) confirms that when AI-PM is implemented, organizational readiness investments significantly enhance project outcomes.

Strategic Conclusion:

The varying support rates reveal a coherent pattern: organizational factors are necessary but insufficient for project success. Infrastructure and workforce development drive AI-PM adoption, and AI-PM adoption is the essential mechanism through which these factors translate into superior project outcomes. Organizations seeking improvement must address both organizational readiness AND AI-PM implementation; skipping either step will undermine improvement efforts. The 84-88% mediation finding emphasizes that AI-PM implementation is not optional but rather a strategic imperative for achieving project management performance improvement.

4.8 Interpretation and Implications of the Mediation Effect

The structural equation modeling results show that AI-Based Project Management mediates approximately 84% of the total effect of the independent variables on project outcomes.

4.8.1 What this means in practical terms:

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

- Infrastructure compatibility

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

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

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

4.8.2 Theoretical implications:

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

4.8.3 Practical implications for organizations:

- Improving enabler readiness alone, such as providing workforce training or updating infrastructure, will not significantly improve project outcomes unless these improvements translate into real AI utilization.
- It is crucial that organizations move beyond just preparing for AI and focus on comprehensive AI utilization and integration into project management workflows.
- Change management programs, technical upgrades, and budget allocation must aim toward enabling effective AI usage, not only readiness on paper.

4.8.4 Support from qualitative evidence:

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

4.9 Qualitative Thematic Analysis

The presented qualitative analysis demonstrates a clear depth in exploring the factors influencing AI utilization in project management within Saudi organizations, with a focus on independent variables (IVs), mediating variables (MVs), and dependent variables (DVs). Several key academic observations can be drawn:

The qualitative analysis demonstrates a clear integration of **technical, organizational, and ethical dimensions** in AI utilization for project management.

Relying on evidence from interviews and representative quotes illustrates a **methodical academic approach**, ensuring result validity and providing a comprehensive view of the dominant factors in AI utilization.

It can be concluded that successful AI utilization requires an **integrated management approach**, combining training, technical compatibility, ethical governance, and financial planning, while considering the local cultural and organizational context.

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

The results indicate that **data privacy and security, ethical concerns, and resistance to change** are among the most prominent factors influencing AI utilization. It is evident that organizations address these factors rigorously through the utilization of **strict governance frameworks, advanced encryption standards, and compliance with local regulations such as SDAIA and SFDA**, reflecting a deep understanding of the importance of security and regulatory compliance in fostering digital trust.

Resistance to change emerges as a fundamental psychological and organizational factor, with initial reluctance linked to unfamiliarity with AI tools and fears of job displacement. Internal training sessions and hands-on workshops play a critical role in reducing this resistance.

Implementation cost and compatibility with existing infrastructure are crucial strategic and technical considerations. Decisions to adopt AI are closely tied to expected ROI, system upgrades, or integration with legacy systems, highlighting the need for long-term planning to manage financial and technical resources effectively.

Workforce development and ethical considerations appear as essential requirements to ensure sustainable and responsible AI use, through continuous training, enhanced analytical capabilities, and ethical governance encompassing transparency and bias mitigation.

To complement the quantitative hypothesis testing, qualitative interviews with 10 expert practitioners were analyzed to understand how organizational factors influence AI adoption in practical, contextual detail. **Table (69)** presents the thematic summary for independent variables, documenting the six key themes that emerged across all interviews: Data Privacy & Security, Change Resistance, Cost of AI Implementation, Compatibility with Existing Infrastructure, Workforce Development, and Ethical Considerations. For each theme, the table documents frequency across interviews, representative quotes, and interpretive summaries. This qualitative analysis provides rich contextual understanding of how these organizational factors manifest in real-world project environments and validates the quantitative findings through practitioner voices

Table (69) Independent Variables (IVs) Thematic Summary Table



Independent Variables (IVs) Thematic Summary Table

No.	Theme	Frequency (Count of Interviews)	Interview IDs with Theme	Recurring Phrases	Representative Quote	Summary Representative Quote
1	Data Privacy & Security	10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	"data privacy", "confidentiality", "regulations"	1. Interview 1: Our primary concern has been maintaining client confidentiality. We first tested localized tools before using larger, cloud-based systems. We set up strict access controls, encrypted shared databases, and trained employees on secure data handling procedures. Data compliance with Saudi regulations is a constantly moving target. 2. Interview 2: Privacy is definitely on everyone's radar. At first, people didn't really know what the tools could do. We align all our tools with Saudi SDAIA data governance regulations — it's now standard practice. 3. Interview 3: Data privacy isn't a barrier anymore but more like a necessary discipline for digital trust. 4. Interview 4: Data privacy is a big concern, especially because we rely a lot on sharing files via third-party apps that sometimes feel insecure. Because of privacy worries, we're careful about which AI tools we allow, preferring well-known vendors. 5. Interview 5: We follow strict compliance with SDAIA and SFDA data policies. 6. Interview 6: Data privacy is always a concern, especially with sensitive design data and client information. Compliance with internal and national data governance is non-negotiable. We	Strict data privacy and security; through encryption, access controls, compliance with SDAIA and international standards, and a culture of continuous vigilance—are universally recognized as essential for AI adoption in project management across Saudi organizations. Maintaining client confidentiality, protecting sensitive project data, and rigorous regulatory compliance are foundational requirements for digital transformation and stakeholder trust

					implemented strict access controls, encrypted file transfers, and cloud governance aligned with SDAIA guidelines. 7. Interview 7: We enforce strict data governance frameworks compliant with regional regulations, ensuring encrypted data pipelines and access controls. Privacy concerns drive our architecture; we use federated learning approaches so data remains local if needed. 8. Interview 8: Data privacy and compliance are always a foundational concern, especially in cloud deployments. Our recommendations emphasize encrypted data flows and sovereign data hosting. 9. Interview 9: Privacy is a priority, so we use encryption and anonymization wherever possible. These concerns make tool selection rigorous, mandating compliance checks. 10. Interview 10: We're cautious about data sharing, especially client confidential info. Privacy concerns slow down some AI adoptions, but security protocols help mitigate risks. We use encryption and strict permissions.	
2	Change Resistance	10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	"fear of AI", "staff hesitant", "pushback"	1. Interview 1: Yes, initially, several engineers resisted AI-driven tools because they feared job redundancy. The main reason was unfamiliarity and lack of training—they didn't understand how AI complements, rather than replaces, their work. We launched internal awareness sessions and hands-on workshops where team members could practice with AI features. Once they saw efficiency gains, resistance dropped significantly. 2. Interview 2: Yeah, at first there was pushback, especially from older engineers. Everyone started	Initial resistance to AI adoption was common, rooted in fears of job redundancy, discomfort with new technologies, and lack of digital literacy, especially among older staff. However, targeted training, leadership engagement, and demonstrated efficiency gains played a crucial role

					to come around once they saw real results. Resistance is now significantly lower. 3. Interview 3: Resistance came mainly from senior managers unfamiliar with digital tools. The hesitation stemmed from mindset gaps. 4. Interview 4: Resistance is quite high, especially among older staff accustomed to manual methods. Fear that AI might replace jobs still exists. 5. Interview 5: Resistance appeared mainly from traditional project managers unfamiliar with AI dashboards. 6. Interview 6: Some resistance exists, mainly from senior engineers used to conventional tools. 7. Interview 7: Resistance stems from lack of AI literacy and concerns about transparency and job displacement. 8. Interview 8: Resistance often stems from organizational mindset rather than technology gaps. Leadership workshops help build AI literacy. 9. Interview 9: Resistance emerged mostly from mid-level engineers uncomfortable with rapid changes. 10. Interview 10: Some staff showed natural resistance initially due to unfamiliarity, but training helped overcome skepticism.	in reducing skepticism and encouraging acceptance across project teams.
3	Cost of AI Implementation	8	1, 2, 3, 5, 6, 7, 8, 9	“budget limitation”, “ROI”, “high cost”	1. Interview 1: Senior management hesitated to invest in AI tools before seeing proven ROI. We assess costs in relation to savings on man-hours and operational efficiency improvements. A feasibility study is conducted before adoption; we only approve tools with tangible project-level impact. AI budgets are part of our annual digital transformation strategy, reviewed every quarter.	Investment in AI tools is carefully weighed against expected efficiency gains, with senior management prioritizing clear ROI, operational impact, and tangible deliverables. Adoption typically advances

					2. Interview 2: For example, one simulation tool basically cuts weekly planning hours in half. If ROI isn't evident within a few projects, we drop the tool. 3. Interview 3: AI initiatives are long-term investments, not quick fixes. Cost evaluation includes not only immediate profit but strategic return. 4. Interview 5: Our concern mainly lies in ensuring secure data storage and avoiding cross-border data leaks. These concerns didn't stop us; we implemented encrypted data layers and internal cloud storage. 5. Interview 6: Budget is a key limiting factor—AI investments compete with tangible project deliverables. We justify adoption when there's a clear link to cost or schedule efficiency. 6. Interview 7: We use rigorous forecasting and risk analysis for financial approvals, balancing investment with long-term operational efficiencies. 7. Interview 8: We advise clients on total cost of ownership, including infrastructure, licensing, and human capital. Investment justification includes long-term digital transformation benefits. 8. Interview 9: Budgeting includes detailed cost-benefit forecasts. Investments are planned through phased rollouts to manage costs.	only when cost-benefit analyses, phased rollouts, and strategic returns justify both immediate and long-term expenditures, making financial prudence central to digital transformation decisions.
4	Compatibility with Existing Infrastructure	9	1, 2, 4, 5, 6, 7, 8, 9, 10	"legacy systems", "integration was difficult"	1. Interview 1: Integration was difficult at first; our legacy systems didn't support APIs for AI tools. Most challenges were related to data format conversion and software interoperability. Upgraded internal systems and migrated to cloud servers, which delayed deployment but made the environment ready for AI utilization.	Integration of AI tools faces significant challenges due to legacy systems that lack API support, data format incompatibilities, and siloed architectures. Organizations often undergo costly and

					2. Interview 2: Learned early lessons; budgeting AI is standard in yearly investments. 3. Interview 4: Some communication platforms have AI features but are underutilized. 4. Interview 5: Compatibility issues mainly due to secure data storage, cross-border data concerns addressed by encryption and cloud controls. 5. Interview 6: Integration with legacy systems still challenging; data formats misaligned. Upgraded servers and cloud storage improved performance but increased timelines and costs. 6. Interview 7: Legacy integration addressed with APIs and cloud strategies; infrastructure modernization aligned with AI roadmap. 7. Interview 8: Expected efficiency gains and risk mitigations quantified, investment justified by ROI and business impact. 8. Interview 9: Legacy system integration required IT planning and network upgrades; ongoing integration remains complex. 9. Interview 10: Legacy system issues handled with middleware and cloud migration, causing extended timelines but improved reliability and uptime.	time-extensive infrastructure upgrades—such as migrating to cloud platforms, modernizing servers, and adopting middleware solutions—to enable AI deployment. Despite initial delays and complexity, these efforts are foundational for unlocking AI's operational benefits and ensuring scalable, reliable digital transformation.
5	Workforce Development	10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	“training”, “skill gaps”, “data interpretation”	1. Interview 1: Not all employees were ready to work with AI tools initially. Skill gaps mainly involved data interpretation and understanding how AI recommendations align with project objectives. We conducted certified training sessions and partnered with a technology institute for in-house courses. The change was noticeable—staff now trust predictive outcomes much more than before. 2. Interview 2: They felt like AI would replace their roles initially. Hesitation came from fear and lack of	Workforce readiness is crucial to successful AI adoption. Initial skill gaps in data interpretation, digital literacy, and trust in AI outputs often cause resistance. Structured, ongoing training programs—including workshops, bootcamps, and

					trust in algorithms. Internal workshops helped alleviate concerns. 3. Interview 3: When AI analytics were introduced, resistance appeared mainly from senior managers unfamiliar with digital systems. The biggest gap was analytical literacy and interpreting AI insights. 4. Interview 4: Training was critical. Practical workshops and management communication improved team acceptance and skills. 5. Interview 5: Focus on continuous professional development programs focused on AI tool utilization and data science principles. 6. Interview 6: Skill gaps included data science proficiency and interpreting algorithm outcomes. Ongoing training is prioritized. 7. Interview 7: Tailored training programs and skill assessments guide individualized learning paths for staff. 8. Interview 8: Workshops include hands-on labs and scenario analysis. Training effectiveness is measured through KPIs. 9. Interview 9: Internal AI Bootcamps and practical dashboards training increased AI competency. 10. Interview 10: Employee AI competency noticeably improved, especially decision support and reporting automation.	tailored learning paths—significantly improve staff competency and acceptance, enabling personnel to leverage AI as a supportive tool rather than a threat to job security.
6	Ethical Considerations	10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	“SDAIA compliance”, “accountability”, “bias”	1. Interview 1: We set up strict access controls, encrypted shared databases, and trained employees on secure data handling procedures. Data compliance with Saudi regulations is a constantly moving target. 2. Interview 2: AI should always be a reference, not the final word. Vendors need to make their	Ethical and legal accountability is foundational in AI adoption, requiring strict compliance with Saudi SDAIA and SFDA data governance laws. Organizations

					algorithms more transparent. We align all our tools with Saudi SDAIA data governance regulations — now standard practice. 3. Interview 3: We handle valuable project and client data, so compliance checks are mandatory. Privacy concerns initially caused hesitation. 4. Interview 4: Accountability for AI errors falls on project leads and managers. Bias is a concern due to local nuances. 5. Interview 5: We actively comply with SDAIA and SFDA data policies, including encrypted file transfers and secure cloud governance. 6. Interview 6: Ethical accountability is integrated with governance frameworks including fairness, audit trails, and transparency. 7. Interview 7: Bias detection and mitigation are part of model lifecycle. Human oversight is mandatory. 8. Interview 8: Compliance with SDAIA and international standards is rigorously maintained throughout deployment. 9. Interview 9: Transparency initiatives involve documenting AI logic and decision pathways in audit logs for traceability. 10. Interview 10: We demand vendor transparency about AI model training data and embed ethics in AI governance.	emphasize transparency, bias mitigation, human-in-the-loop oversight, and vendor accountability. Embedding these ethical principles throughout AI development and deployment fosters regulatory compliance, stakeholder trust, and sustainable AI integration aligned with national and global standards.
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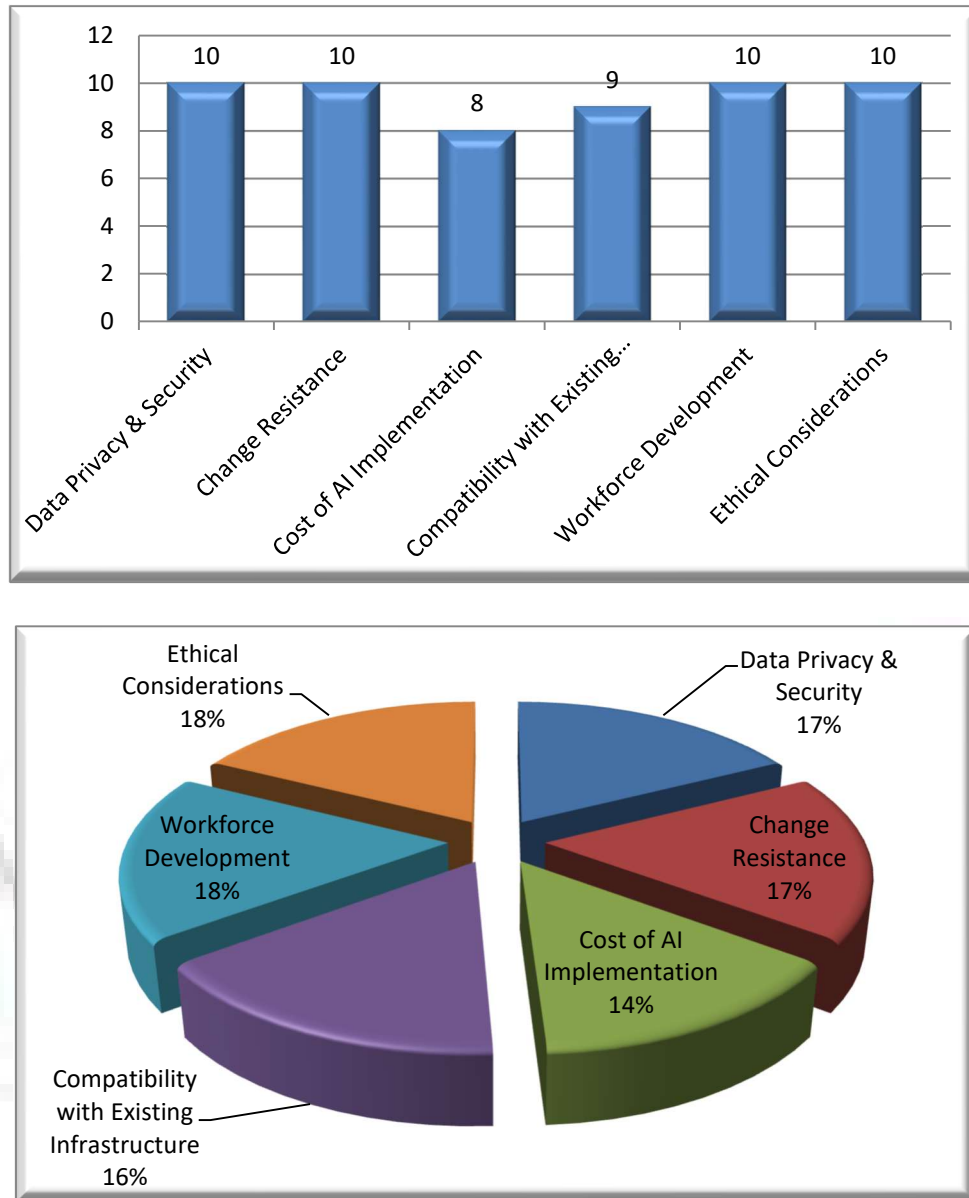


Figure (11): Frequency and Percentage of Independent Variables (IVs)

4.9.2 Mediating Variables (AI-Based Project Management) - 5 Themes

All five mediating variable themes were identified, representing dimensions of AI-based PM utilization:

The analysis shows that AI contributes to improving operational efficiency through **process automation, better resource allocation, task prioritization**, as well as enhancing **progress tracking, reporting, and team communication**.

These findings highlight AI’s mediating role in transforming management strategies into **data-driven decisions**, suggesting that the influence of independent variables on outcomes is often indirect and relies on mediating factors such as operational efficiency and communication.

Complementing the quantitative mediation analysis, qualitative interviews explore how AI-based project management actually operates as a mediating mechanism in practice. **Table (70)** presents the thematic summary for mediating variables, documenting five core themes that emerged across practitioner interviews: Streamlining Process (10/10 interviews), Resource Allocation (9/10), Task Prioritization (4/10), Progress Reporting (10/10), and Communication (10/10). For each theme, the table documents interview frequency, specific sources, representative quotes, and interpretive summaries. This qualitative analysis reveals the practical dimensions through which AI-PM adoption transforms organizational factors into project improvements, providing rich contextual understanding of the mediation mechanism validated by quantitative findings.

Table (70) Mediating Variables (MVs) Thematic Summary Table



Mediating Variables (MVs) Thematic Summary Table

No.	Theme	Frequency	Interview IDs with Theme	Recurring Phrases		Representative Quote
1	Streamlining Process	10	1,2,3,4,5,6,7,8,9,10	“streamline”, “automation”, “efficiency”	1. Interview 1: We use AI to automate scheduling and report generation. Previously, progress reports required two days of manual compilation; now they’re ready in hours. AI helps standardize documentation and reduces repetitive administrative tasks. It has improved execution efficiency overall, though adjustments during early integration were challenging. 2. Interview 2: It frees a lot of mental load. For instance, our AI scheduling assistant allocates resources automatically while considering lead times. Project tracking has become smoother with less back-and-forth communication. 3. Interview 3: Report generation that used to take days now happens in minutes through automated systems. The workflow visibility has improved significantly — I can oversee progress from my dashboard. Efficiency and transparency gains are substantial.	AI automation transforms project management by significantly reducing the time spent on routine scheduling and report generation—from days to hours or even minutes. It standardizes documentation, cuts repetitive administrative tasks, and enhances workflow visibility through real-time dashboards. These efficiencies decrease mental workload, smooth project tracking, reduce communication overhead, and accelerate decision-making, creating substantial transparency and productivity gains despite early integration challenges

					4. Interview 4: Some communication platforms have AI features, but we're not fully utilizing them. 5. Interview 5: AI automates many administrative tasks, improving accuracy and throughput. 6. Interview 6: Automated report generation and data aggregation accelerate decision support. 7. Interview 7: Real-time dashboards improve project monitoring and help mitigate delays. 8. Interview 8: AI-driven tools pull together updates automatically which saves effort. 9. Interview 9: Scheduling errors have reduced due to automatic reminders and task allocations. 10. Interview 10: Automated workflows and report generation created noticeable efficiency improvements.	
2	Resource Allocation	9	1,2,3,4,6,7,8,9,10	"optimize staff", "data-driven", "allocation"	1. Interview 1: AI budgets are part of our annual strategy. We assess costs against savings in operational efficiency and man-hours. Resource allocation has become data-driven and over-allocation decreased by nearly 20%.	AI significantly enhances resource allocation by leveraging data-driven forecasting, predictive analytics, and real-time adaptability. It helps optimize manpower and materials allocation, reduce

					2. Interview 2: AI identifies resource clashes faster and allocates resources automatically considering lead times. Resource planning is more accurate, reducing delays. 3. Interview 3: AI helps ensure proper resource utilization and highlights idle assets and manpower. Operations have become leaner with better manpower forecasting. 4. Interview 4: Some AI-powered communication and resource systems are available but underutilized. 5. Interview 5: AI supports optimal workload distribution and forecasting manpower needs, improving visibility across disciplines. 6. Interview 6: AI optimizes resource allocation by considering historical data and real-time inputs, improving efficiency. 7. Interview 7: Using advanced AI for predictive analytics and risk simulations to enhance resource deployment. 8. Interview 8: Resource planning is increasingly data-driven with AI forecasts improving scheduling.	over-allocation by nearly 20%, detect resource clashes faster, and match tasks to the right skills—resulting in leaner operations, fewer delays, and improved cross-disciplinary visibility. Continuous automation and intelligent planning empower managers to make more accurate, timely, and flexible resource decisions.
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					9. Interview 9: AI-based planning optimizes manpower and materials allocation, increasing resource utilization and accuracy.	
3	Task Prioritization	4	3,6,8,9	"prioritize", "reallocate"	1. Interview 3: AI scheduling tools prioritize tasks better than humans under pressure. The system flagged conflicting deadlines early, allowing timely corrections. 2. Interview 6: AI helps prioritize tasks by analyzing dependencies and critical paths, preventing overlaps and ensuring focus on critical items. 3. Interview 8: AI supports dynamic task prioritization based on risk, improving efficiency and reducing project delays. 4. Interview 9: Early warnings from AI tools prevent bottlenecks by proactively adjusting priorities.	AI-enabled task prioritization systems outperform manual methods by dynamically analyzing task dependencies, urgency, and risk factors. These systems proactively flag conflicting deadlines and bottlenecks, enabling timely adjustments that prevent overlaps, improve focus on critical activities, and reduce overall project delays. Dynamic reprioritization minimizes decision fatigue and supports more efficient workflow management under pressure.
4	Progress Reporting	10	1,2,3,4,5,6,7,8,9,10	"report", "alerts", "consolidate"	1. Interview 1: We use AI to automate scheduling and report generation. Previously, progress reports required two days of manual compilation; now they're ready in hours. AI standardizes documentation and reduces	AI-enabled task prioritization systems outperform manual methods by dynamically analyzing task dependencies, urgency, and risk factors. These

					repetitive tasks, improving execution efficiency overall. 2. Interview 2: AI consolidates multiple inputs and provides early alerts which caught delays early, avoiding escalation. 3. Interview 3: Report generation now takes minutes, and dashboards provide clear workflow visibility improving execution and transparency. 4. Interview 4: AI-driven dashboards consolidate data and generate weekly updates automatically. 5. Interview 5: Automated report generation accelerates decision support and reduces errors. 6. Interview 6: Predictive alerts help identify slippages early and enable proactive adjustments. 7. Interview 7: AI tools facilitate timely collaboration and structured communication with stakeholders. 8. Interview 8: AI assists in generating reports with visuals and charts, saving time. 9. Interview 9: Field data capture and validation ensure reporting accuracy and reliability. 10. Interview 10: Early alerts and consolidated real-time data	systems proactively flag conflicting deadlines and bottlenecks, enabling timely adjustments that prevent overlaps, improve focus on critical activities, and reduce overall project delays. Dynamic reprioritization minimizes decision fatigue and supports more efficient workflow management under pressure.
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					feeds improve project progress monitoring.	
5	Communication	10	1,2,3,4,5,6,7,8,9,10	“coordinate”, “dashboard”, “meeting”	1. Interview 1: Everyone now uses a common dashboard. Even stakeholder meetings rely on AI summaries to keep discussions focused. 2. Interview 2: I coordinate between design and site teams, ensuring smooth operations. AI dashboards and risk models training helped make meetings shorter and decisions more data-driven. 3. Interview 3: AI tools facilitate timely collaboration and data-driven communication. 4. Interview 4: Some communication platforms have AI features, but are underutilized. 5. Interview 5: Automated meeting summaries and stakeholder updates save administrative time. 6. Interview 6: AI-enabled platforms have improved team communication through automated notifications. 7. Interview 7: AI-powered	AI automates scheduling and report generation, drastically reducing turnaround times from days to hours or minutes. It standardizes documentation, reduces repetitive administrative tasks, and improves workflow visibility through real-time dashboards, accelerating decision-making and mitigating delays. Although some communication platforms remain underutilized, AI-driven tools like automated updates and notifications significantly enhance team coordination, reduce errors, and streamline stakeholder engagement.

					communication channels reduce misunderstandings and enhance stakeholder engagement. 8. Interview 8: AI bots and virtual assistants foster timely updates and clear communication. 9. Interview 9: Real-time collaboration and automated updates improve response times and stakeholder trust. 10. Interview 10: AI tools reduce manual follow-ups and enhance transparency in client updates	
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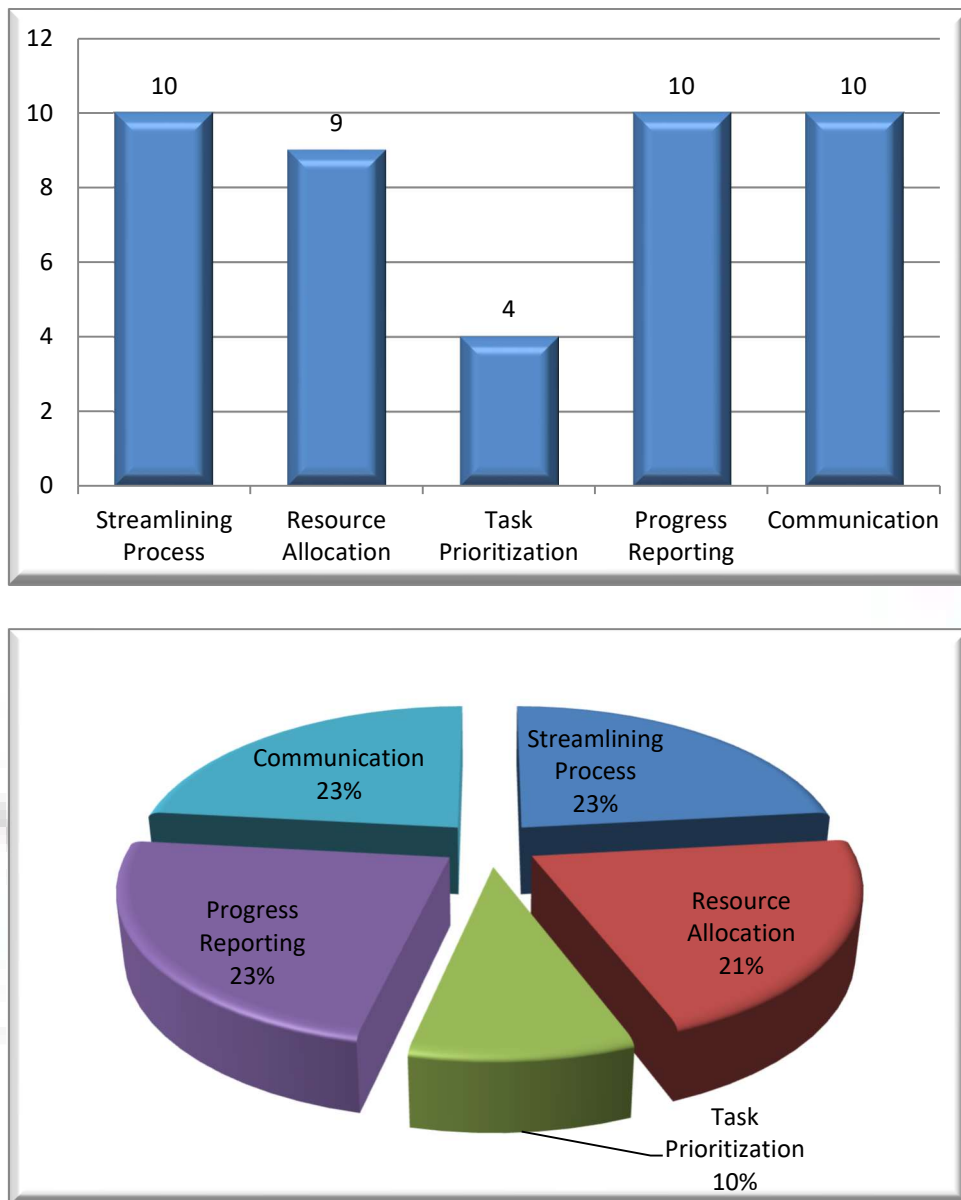


Figure (12): Frequency and Percentage of Mediating Variables (MVs)

4.9.3 Dependent Variables (Project Management Outcomes) - 7 Themes

All seven dependent variable themes were prominently featured across interviews:

The results indicate that **project quality, data collection accuracy, enhanced analytics, early risk identification, time savings, and improved communication** are all positively influenced by AI implementation.

This reflects that AI's role goes beyond mere automation, adding **cognitive and strategic value** by supporting decision-making, improving quality monitoring, and enabling project managers to focus on strategic and innovative aspects.

To complement the quantitative finding that AI-PM produces universal benefits across all seven outcome dimensions, qualitative interviews explore how practitioners experience these improvements in real project environments. **Table (71)** presents the thematic summary for dependent variables, documenting seven core themes that emerged with universal frequency: Improving Project Quality (10/10 interviews), Enhancing Decision-Making (10/10), Data Collection Accuracy (10/10), Enhancing Data Analysis (10/10), Risk Identification Accuracy (10/10), Saving Time for Project Managers (10/10), and Enhancing Communication (10/10). For each theme, the table documents interview frequency, specific sources, representative quotes, and interpretive summaries. This qualitative analysis reveals the tangible, practical benefits of AI-PM adoption experienced across all project management dimensions

Table (71) Dependent Variables (DVs) Thematic Summary Table



Dependent Variables (DVs) Thematic Summary Table

No.	Theme	Frequency	Interview IDs with Theme	Recurring Phrases		Representative Quote
1	Improving Project Quality	10	1,2,3,4,5,6,7,8,9,10	"quality", "error detection", "accuracy"	1. Interview 1: Quality control benefited from early error detection during design reviews. AI budgets are part of the digital transformation strategy. 2. Interview 2: AI-based design optimizers and risk forecasting applications improve quality and save time. 3. Interview 3: Automated inspection reports improved quality checks; client satisfaction increased with transparent reporting. 4. Interview 4: AI-driven dashboards flag delayed deliverables and improve traceability. 5. Interview 5: Accuracy in schedule adherence and deliverable quality has measurably improved. 6. Interview 6: AI-generated dashboards enhanced confidence and reduced manual errors. 7. Interview 7: Predictive analytics help detect quality risks early and aid in project delivery consistency. 8. Interview 8: Forecasts and data-backed feedback loops refine quality assurance. 9. Interview 9: Documentation errors	AI enhances project quality through early error detection, automated inspections, and predictive analytics that improve accuracy, traceability, and client satisfaction. By reducing manual errors and facilitating continuous quality monitoring, AI strengthens compliance and delivers consistent, transparent project outcomes, boosting stakeholder trust and driving sustained quality improvements.

					dropped significantly; reporting accuracy improved. 10. Interview 10: Clients recognize enhanced credibility in AI-generated reports, with continuous quality improvements.	
2	Enhancing Decision-Making	10	1,2,3,4,5,6,7,8,9,10	“decision”, “data-driven”, “accuracy”, “delay”	1. Interview 1: Decision accuracy improved as AI correlates cost, risks, and timelines. AI budgets are part of our digital strategy reviewed quarterly. 2. Interview 2: AI helps avoid delays by flagging scheduling conflicts. Decisions are faster and more data-driven. 3. Interview 3: AI enables evidence-backed decisions that keep projects on track with higher consistency. 4. Interview 4: Leadership uses AI dashboards to set the tone and promote fast, data-informed decisions. 5. Interview 5: AI analytics improved decision accuracy and consistency, reducing manual errors. 6. Interview 6: AI decision support reduces subjective errors and increases decision speed. 7. Interview 7: AI-based risk analysis prevents resource overcommitment and optimizes decisions. 8. Interview 8: Predictive analytics assists in faster, more accurate	AI significantly improves decision accuracy, speed, and consistency in project management by correlating complex data on costs, risks, and timelines. Leadership increasingly relies on AI-driven dashboards and predictive analytics to make faster, evidence-based decisions that keep projects aligned with strategic goals and reduce idle time and manual errors.

					project decisions. 9. Interview 9: AI insights lead to timely, consistent decision-making aligned with project goals. 10. Interview 10: Faster validated decisions reduce idle time and improve project delivery.	
3	Data Collection Accuracy	10	1,2,3,4,5,6,7,8,9,10	“data collection”, “logs”, “error reduction”	1. Interview 1: All project data is now captured through digital logs instead of manual sheets. Data duplication errors reduced by 80%. Documentation errors dropped significantly. 2. Interview 2: AI-based data collection tools and automated scheduling software improve accuracy and reduce manual efforts. 3. Interview 3: Field data capture via mobile AI apps reduced manual entry errors. Real-time validation catches anomalies. 4. Interview 4: AI helps standardize documentation and improves consistency. 5. Interview 5: Reliable data supports executive decisions through automated pipelines. 6. Interview 6: AI cross-verifies entries, greatly improving confidence in data accuracy. 7. Interview 7: Automated validation checks and data integrity tools boost reporting reliability.	AI-driven automation of data capture and validation significantly minimizes manual entry errors, data duplication, and inconsistencies across project documentation. Real-time anomaly detection, digital logs, and automated pipelines build higher confidence in data integrity, enabling more reliable executive decision-making, planning, and reporting.

					8. Interview 8: Error margins decreased significantly with AI automation. 9. Interview 9: Data collection systems reduce loss and mismatch risks. 10. Interview 10: Reporting accuracy improved for better planning and executive reviews.	
4	Enhancing Data Analysis	10	1,2,3,4,5,6,7,8,9,10	“analysis”, “predictive analytics”	1. Interview 1: AI helps understand project risk and cost patterns that manual analysis missed. It supports forecasting and risk planning. 2. Interview 2: Predictive analytics and data visualization tools support decision-making and project planning. 3. Interview 3: Complex risk and cost patterns are detected early; inefficiencies identified and addressed. 4. Interview 4: Forecast accuracy enables better planning and risk management. 5. Interview 5: Executives trust AI-driven forecasts for operational reviews. 6. Interview 6: Forecasts derived from AI tools are reliable and improve decision quality. 7. Interview 7: Forecasting models underpin risk and timeline management.	AI-driven predictive analytics and data visualization uncover complex risk and cost patterns often missed by manual analysis. These tools enable early detection of inefficiencies and risks, improve forecast accuracy, and support strategic resource optimization and operational adjustments. Executives increasingly trust AI-derived insights for planning and continuous improvement

					8. Interview 8: AI reveals inefficiencies and flags risks, aiding continuous improvement. 9. Interview 9: Analytics uncover hidden cost patterns and optimize resource use. 10. Interview 10: Data-backed insights drive strategic adjustments and operational efficiency.	
5	Risk Identification Accuracy	10	1,2,3,4,5,6,7,8,9,10	“risk”, “early warning”, “flag”	1. Interview 1: AI systems flag potential delay risks early. Early alerts help detect slow progress, allowing mitigation. 2. Interview 2: AI-generated risk maps guide mitigation planning and highlight vendor capacity risks. 3. Interview 3: AI predictive alerts prevent bottlenecks through early task reprioritization. 4. Interview 4: Workload-based bottleneck predictions enhance resource deployment. 5. Interview 5: Proactive mitigation steps based on AI insights refine risk culture. 6. Interview 6: Dynamic risk indicators enable agile project responses. 7. Interview 7: AI helps identify supplier delay risks and supports weekly risk mitigation. 8. Interview 8: Early risk identification has prevented major	AI significantly improves risk identification accuracy by providing early predictive alerts, dynamic risk maps, and workload-based bottleneck forecasting. These capabilities enable proactive mitigation, prevent schedule and supply chain disruptions, and foster a data-driven risk culture that enhances project resilience and agility.

					issues in procurement and scheduling. 9. Interview 9: System predictive alerts now prevent sudden surprises. 10. Interview 10: AI-driven risk culture fosters preventive actions and improves project resilience.	
6	Saving Time for Project Managers	10	1,2,3,4,5,6,7,8,9,10	“time”, “save hours”, “automation”	1. Interview 1: AI automation reduced time spent on reports and documentation, saving 8–10 hours weekly per manager. 2. Interview 2: AI tools balance cost against time saved, significantly improving efficiency. 3. Interview 3: Weekly updates auto-generated, reducing administrative burden and improving focus. 4. Interview 4: AI eliminated much manual tracking and sped coordination. 5. Interview 5: Automated report generation significantly cuts manual work. 6. Interview 6: More time now goes into strategic coordination and innovation. 7. Interview 7: AI tools save time spent on routine tasks and enable faster decision-making. 8. Interview 8: Time saved is reinvested in innovation and high-value tasks.	AI automation significantly reduces the time managers spend on routine reporting, documentation, and manual tracking—saving up to 8–10 hours weekly per manager in some cases. By automating status updates, consolidating information, and streamlining communication, AI enables managers to focus more on strategic coordination and innovation, accelerating decision-making and improving overall project outcomes.

					9. Interview 9: Communication delays decreased due to AI assistance. 10. Interview 10: Leadership leverages saved time for strategic focus and better project outcomes.	
7	Enhancing Communication	10	1,2,3,4,5,6,7,8,9,10	“collaboration”, “dashboard”, “communication”	1. Interview 1: AI-enabled dashboards and communication platforms improve coordination between on-site and design teams, with automated meeting summaries. 2. Interview 2: AI tools summarize meeting discussions and action items, enhancing team alignment. 3. Interview 3: Virtual assistants and AI bots facilitate timely stakeholder engagement and clear data-driven communication. 4. Interview 4: Automated reporting and notifications reduce misunderstandings and keep teams synchronized. 5. Interview 5: Stakeholder meetings rely on AI summaries for focused discussions. 6. Interview 6: Team communication is fluid, with faster response times and fewer missed updates. 7. Interview 7: AI supports instant client updates and transparent project portals. 8. Interview 8: Automated meeting notes and integrated project feeds	AI-powered communication platforms and dashboards streamline coordination between dispersed teams by automating meeting summaries, action item tracking, and status updates. These tools reduce communication delays, minimize misunderstandings, and promote transparent, real-time collaboration—building stronger trust among stakeholders and enabling more focused, data-driven project discussions.

					increase communication efficiency. 9. Interview 9: Clients appreciate quick and transparent updates through AI-driven portals. 10. Interview 10: Reduced manual follow-ups and improved transparency have built stronger stakeholder trust.	
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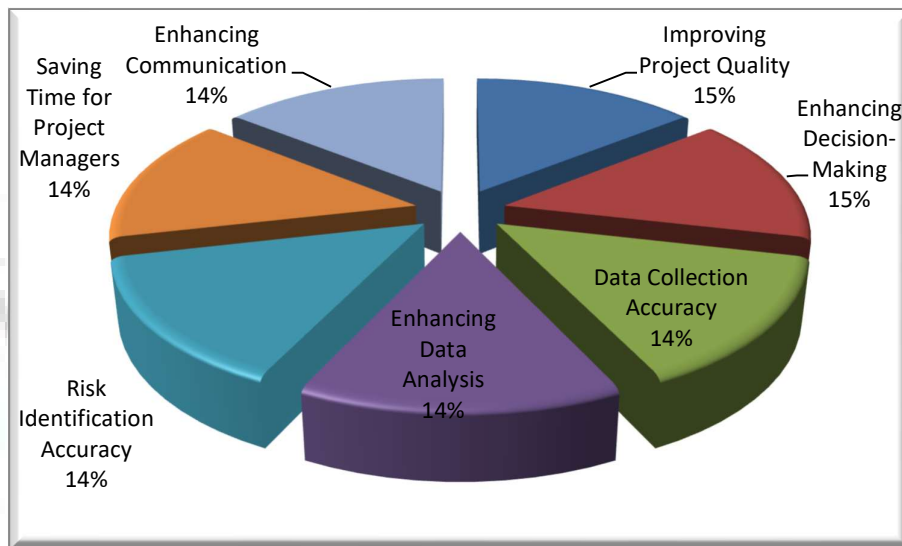
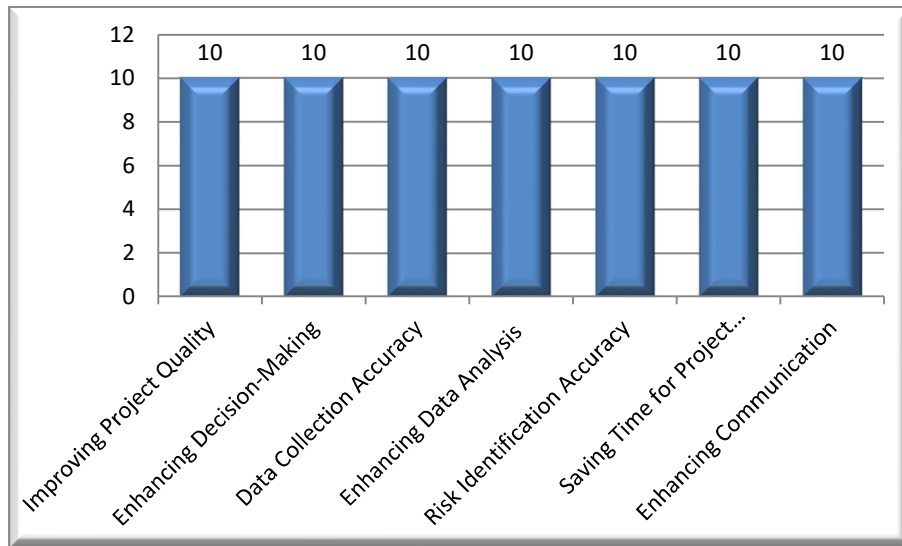


Figure (13): Frequency and Percentage of Dependent Variables (DVs)

4.10 Integration of Quantitative and Qualitative Findings (Triangulation)

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

4.10.1 Convergence Between Methods

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

1. Workforce Development Impact

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

2. Time Savings Outcome

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

3. Data Quality & Analysis

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

4. Infrastructure Compatibility Barriers

- Quantitative: Strong Independent Variables to Mediating Variable correlation ($r = 0.521$); significant direct effect ($B = 2.278$, $p = 0.001$)
- Qualitative: 100% of interviews cited integration challenges; specific systems mentioned (Primavera, Revit, SAP)

- Integration: Infrastructure emerges as validated barrier across methods

4.10.2 Discrepancies and Contextual Explanations

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

1. Ethical Considerations Discrepancy:

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

2. Cost as Non-Significant Predictor:

- Quantitative: Significant correlation with AI-Based Project Management ($r = 0.325$) but not direct outcome effect ($p = 0.557$)
- Qualitative: Cost mentioned in 100% of interviews; frequently cited as barrier
- Explanation: Cost influences AI utilization (hence correlation with AI-Based Project Management), but firms that utilize despite cost constraints achieve comparable outcomes to well-funded organizations. This suggests cost is a barrier to entry, not a determinant of performance.

4.10.3 Mediating Role Validation

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

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

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

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

4.11 Summary of Key Findings

4.11.1 Quantitative Findings:

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

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

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

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

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

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

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

4.11.2 Qualitative Findings:

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

Independent Variables (6 themes; 8-10/10 interviews): All six organizational factors—Data Privacy & Security, Resistance to Change, Cost, Infrastructure Compatibility, Workforce Development, and Ethical Considerations—emerged as universally recognized barriers/enablers. Practitioners consistently emphasized infrastructure upgrades and training as critical for adoption success.

Mediating Variables (5 themes; 4-10/10 interviews): Four themes emerged with universal frequency (9-10/10): Streamlining Process (automation reducing report time from days to hours), Resource Allocation (over-allocation reduced ~20%), Progress Reporting (automated alerts catching delays early), and Communication (common dashboards improving coordination). Task Prioritization appeared less frequently (4/10), indicating emerging adoption.

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

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

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

4.11.3 Integrated Findings:

Strong convergence between quantitative and qualitative results:

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

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

4.11.4 Conclusion

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

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

The mediation analysis (H4) represents the core finding: AI-PM fully mediates the relationship between organizational factors and project outcomes, with 84-88% of the influence operating through the mediation pathway. The non-significant direct effect ($\beta=0.125$, $p=0.455$) definitively establishes that organizational readiness factors alone do not automatically produce outcome improvements; rather, these improvements materialize only when organizational readiness catalyzes effective AI-PM adoption and implementation.

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

Practitioners consistently reported tangible improvements: data duplication errors reduced by 80%, project managers saving 8-10 hours weekly, decision accuracy

improved through data-driven dashboards, early risk identification preventing major issues, and enhanced stakeholder trust through transparent communication. These qualitative insights translate the quantitative coefficients into lived organizational reality.

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

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



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