

**EXPLORING THE MODERATING ROLE OF
ARTIFICIAL INTELLIGENCE ON THE IMPACT
OF QUALITY MANAGEMENT ON
CONSTRUCTION PROJECT OUTCOMES**

(A Case Study of Jeddah Stormwater Program)

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List of Abbreviation

AI	Artificial Intelligence
AR	Augmented reality
BIM	Building Information Modelling
CQM	Construction Quality Management
CV	Computer Vision
FMEA	Failure Mode and Effects Analysis
IoT	Internet of Things
ITP	Inspection Testing Plans
JSWP	Jeddah Stormwater Program
ML	Machine Learning
MIR	Material Inspection Request
MOS	Method of Statements
NCR	Non-Conformance Report
NLP	Natural Language Processing
PDCA	Plan Do Check Act
PMO	Project Management Office
PQP	Project Quality Plan
QA	Quality Assurance
QC	Quality Control
QI	Quality Improvement
QMS	Quality Management Systems
SOR	Site Observation Reports
SPC	Statistical Process Control
TQC	Total Quality Control
TQM	Total Quality Management

Chapter Four

Research Results

4.1 Introduction

This chapter the results of the study “Exploring the Moderating Role of Artificial Intelligence on the Impact of Quality Management on Construction Project Outcomes: A case study of the Jeddah Stormwater Program”. The chapter provides a comprehensive account of both quantitative and qualitative findings derived from the mixed-methods design described early on Chapter 3, that was developed by following the guidance and steps explained by Creswell and Plano Clark (2018). The quantitative and qualitative data are first analyzed independently and then interpreted jointly to generate a coherent understanding of the research problem.

The purpose of this chapter is to demonstrate how the collected data supports, refine, or challenges the study’s hypothesis and research questions. The quantitative analysis focuses on responses from construction professionals within JSWP and professional working in similar projects within Saudi Arabia, assessing the relationships between CQM practices, AI adoption, and project outcomes, cost, time, quality, and customer satisfaction. This analysis includes reliability testing, descriptive statistics, correlation analysis, regression modeling, and moderation testing to determine the extent to which AI technologies influence the strength and direction of the relationship between CQM practices and project outcomes, following the procedures recommended by Hair et al. (2021).

Section 4.2 will present the quantitative data analysis, including response rate, demographic profile, and the results of statical tests for each hypothesis. Section 4.3 shows qualitative analysis, integrating themes emerging from program documents, Section 4.4 synthesizes both quantitative and qualitative strands to present the merged interpretation. At the end of the chapter, chapter 4.5 concludes with the summary of finding and its link to the research objectives. Combining these analysis provide an understanding of how the integration of AI can enhance or

moderate the effectiveness of CQM practices in improving project performance and outcomes.

4.2 Quantitative Data Analysis

This section presents the statistical analysis of the quantitative data collected from 187 participants. The analysis follows the structure defined in Chapter 3 and covers descriptive statistics, reliability, validity, correlations, regression testing of the main hypotheses, and the moderation analysis assessing the role of Artificial Intelligence (AI) technologies within the relationship between Construction Quality Management (CQM) practices and project outcomes.

4.2.1 Reliability and validity of the Instrument

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. The higher the value of Cronbach's Alpha (usually ≥ 0.70), the greater the indication that the items consistently measure the same construct.

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.

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.

To ensure the validity and reliability of the data in this research, the questionnaires were designed to represent every aspect of the study objectives.

4.2.1a Reliability and validity for Independent Variables (Construction Quality Management “CQM”)

Table (4-1) Validity and stability coefficients for the study questionnaire variables.			
Variables	Validity coefficient (Pearson Correlation Coefficient)	Stability Coefficient (Cronbach alpha)	
QP1	0.643**	0.877	0.949
QP2	0.780**		
QP3	0.751**		
QP4	0.796**		
QP5	0.800**		
QP6	0.853**		
QP7	0.687**		
Quality Planning	0.889**	0.859	
QA1	0.766**		
QA2	0.669**		
QA3	0.761**		
QA4	0.751**		
QA5	0.838**		
QA6	0.805**		
Quality Assurance	0.894**	0.842	
QC1	0.760**		
QC2	0.777**		
QC3	0.708**		
QC4	0.771**		
QC5	0.803**		
QC6	0.713**		
Quality Control	0.828**	0.900	
QI1	0.829**		
QI2	0.883**		
QI3	0.877**		
QI4	0.875**		
QI5	0.764**		
Quality Improvement	0.882**		
** A function at the level of significance less than (0.01)			

Table (4-1) above presents the validity coefficients (Pearson Correlation Coefficients) and reliability coefficients (Cronbach’s Alpha) for the questionnaire items and variables. It is evident that all values fall within

statistically acceptable ranges, reflecting a high level of quality in the construction of the measurement instrument.

- **Validity Coefficients (Pearson Correlation Coefficient)**

The validity coefficients for all items indicate strong and statistically significant correlations at the 0.01 level with their corresponding variables, with correlation values ranging from 0.643 to 0.894. These high values suggest that the items effectively measure the same concept associated with their respective dimension. Such findings represent an important indicator of validity, supporting the appropriateness of using these items to measure the study variables.

- **Reliability Coefficients (Cronbach's Alpha)**

Cronbach's Alpha values for the main variables were remarkably high, ranging from 0.842 to 0.900. These values exceed the widely accepted minimum threshold of 0.70, "The overall Cronbach's Alpha value for the scale reached (0.949), which is higher than the acceptable threshold of 0.70, indicating that the scale demonstrates a high level of reliability."

4.2.1b Reliability and validity for Mediating Variables (AI)

Table (4-1) Validity and stability coefficients for the study questionnaire variables				
Variables	Validity coefficient (Pearson Correlation Coefficient)	Stability Coefficient (Cronbach alpha)		
AR1	0.530**	0.772	0.852	
AR2	0.483**			
AR3	0.484**			
AR4	0.472**			
AR5	0.479**			
AR6	0.519**			
AR7	0.489**			
AR8	0.532**			
Awareness & Readiness	0.820**			
AI1	0.650**	0.855		
AI2	0.792**			
AI3	0.713**			
AI4	0.772**			
AI5	0.814**			
AI6	0.612**			
AI7	0.717**			
AI8	0.654**			
AI Utilization	0.824**			
C1	0.454**	0.722		
C2	0.497**			
C3	0.587**			
C4	0.553**			
C5	0.438**			
C6	0.566**			
C7	0.409**			
C8	0.685**			
C9	0.590**			
C10	0.665**			
C11	0.287*			
Challenges	0.808**			
** A function at the level of significance less than (0.01)				
* A function at the level of significance less than (0.05)				

The table (4-2) presents the validity coefficients (Pearson Correlation Coefficients) and reliability coefficients (Cronbach's Alpha) for the questionnaire items and variables. It is evident that all values fall within statistically acceptable ranges, reflecting a high level of quality in the construction of the measurement instrument.

- **Validity Coefficients (Pearson Correlation Coefficient)**

The validity coefficients for all items indicate strong and statistically significant correlations at the 0.05 and 0.01 level with their corresponding variables, with correlation values ranging from 0.287 to 0.814. These

high values suggest that the items effectively measure the same concept associated with their respective dimension. Such findings represent an important indicator of validity, supporting the appropriateness of using these items to measure the study variables.

- **Reliability Coefficients (Cronbach's Alpha)**

Cronbach's Alpha values for the main variables were remarkably high, ranging from 0.722 to 0.855. These values exceed the widely accepted minimum threshold of 0.70, "The overall Cronbach's Alpha value for the scale reached (0.852), which is higher than the acceptable threshold of 0.70, indicating that the scale demonstrates a high level of reliability."

4.2.1C Reliability and validity for Dependent Variables (Project Outcomes)

Table (4-3) Validity and stability coefficients for the study questionnaire variables.			
Variables	Validity coefficient (Pearson Correlation Coefficient)	Stability Coefficient (Cronbach alpha)	
Cost1	0.679**	0.701	0.831
Cost2	0.494**		
Cost3	0.889**		
Cost4	0.817**		
project cost	0.792**		
Schedule1	0.665**	0.707	
Schedule2	0.653**		
Schedule3	0.723**		
project schedule	0.473**		
Quality1	0.485**		
Quality2	0.756**	0.712	
Quality3	0.778**		
Quality4	0.755**		
overall project quality	0.798**		
Customer Satisfaction1	0.692**		
Customer Satisfaction2	0.753**	0.781	
Customer Satisfaction3	0.853**		
Customer Satisfaction4	0.816**		
customer satisfaction	0.853**		
** A function at the level of significance less than (0.01)			

The table (4-3) presents the validity coefficients (Pearson Correlation Coefficients) and reliability coefficients (Cronbach's Alpha) for the questionnaire items and variables. It is evident that all values fall within statistically acceptable ranges, reflecting a high level of quality in the construction of the measurement instrument.

- **Validity Coefficients (Pearson Correlation Coefficient)**

The validity coefficients for all items indicate strong and statistically significant correlations at the 0.01 level with their corresponding variables, with correlation values ranging from 0.473 to 0.889. These high values suggest that the items effectively measure the same concept associated with their respective dimension. Such findings represent an important indicator of validity, supporting the appropriateness of using these items to measure the study variables.

- **Reliability Coefficients (Cronbach's Alpha)**

Cronbach's Alpha values for the main variables were remarkably high, ranging from 0.701 to 0.781. These values exceed the widely accepted minimum threshold of 0.70, "The overall Cronbach's Alpha value for the scale reached (0.831), which is higher than the acceptable threshold of 0.70, indicating that the scale demonstrates a high level of reliability."

4.2.2 Respondents' Demographic Information

Table (4-3) shows the Descriptive Analysis of demographic characteristics of the Study sample regarding the respondent's

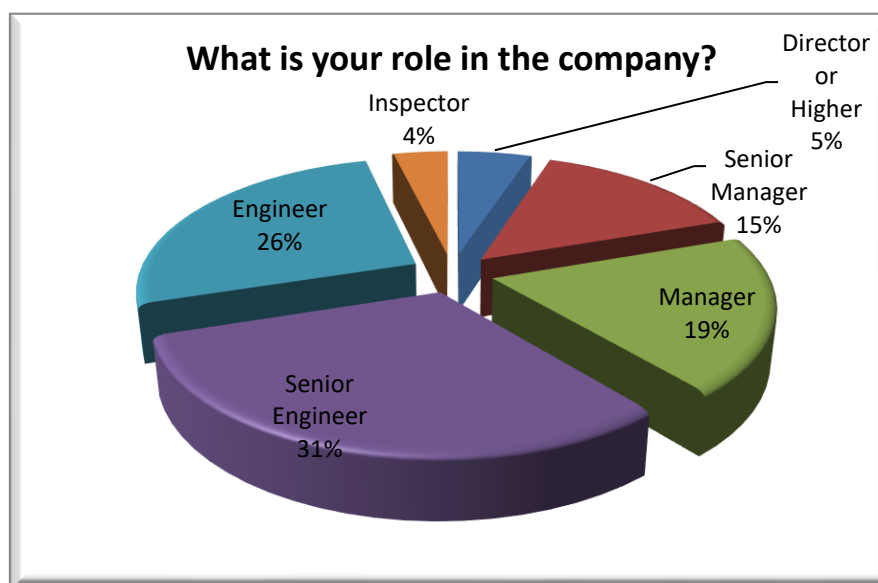
Table (4-3) Descriptive Analysis of Demographic Characteristics of the Study Sample			
Category		Freq.	Percent
What is your role in the company?	Director or Higher	8	5.1
	Senior Manager	23	14.6
	Manager	30	19.1
	Senior Engineer	49	31.2
	Engineer	41	26.1
	Inspector	6	3.8
What is your department?	Management	31	18.6
	Construction	46	27.5
	Quality	41	24.6
	HSE	16	9.6
	Planning/ Cost control	8	4.8
	Technical	13	7.8
	Other	12	7.2
What is the role of your organization in the project?	Client	25	15.0
	PMO / PMC	52	31.1
	Supervision Consultant	49	29.3
	Contractor / Sub-Contractor	38	22.8
	Supplier	3	1.8
How many years of	0 - 5 Years	12	7.2

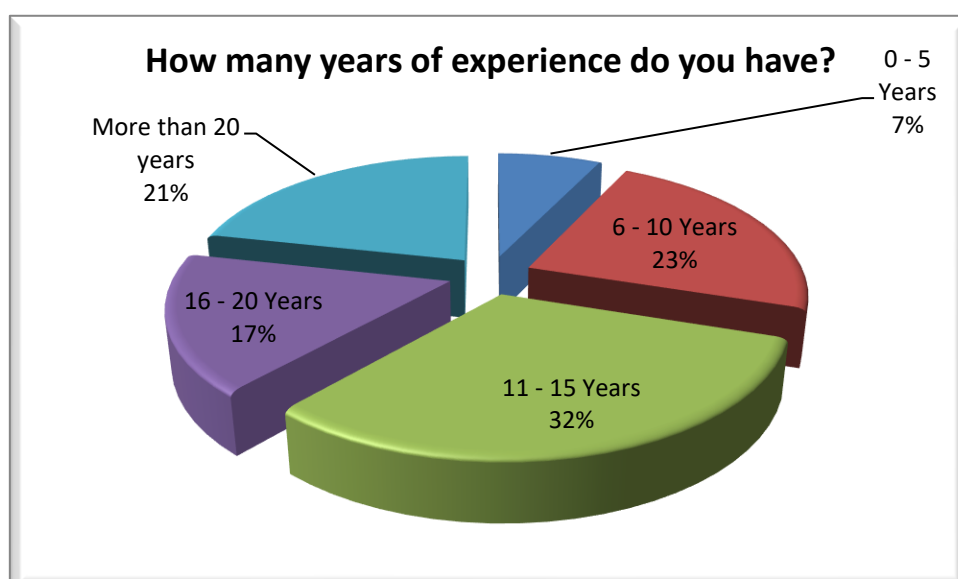
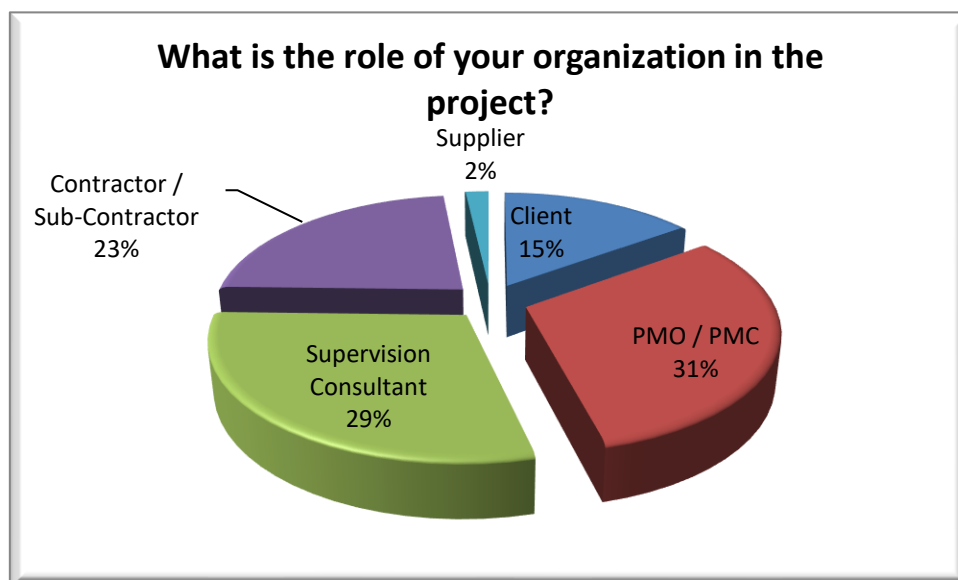
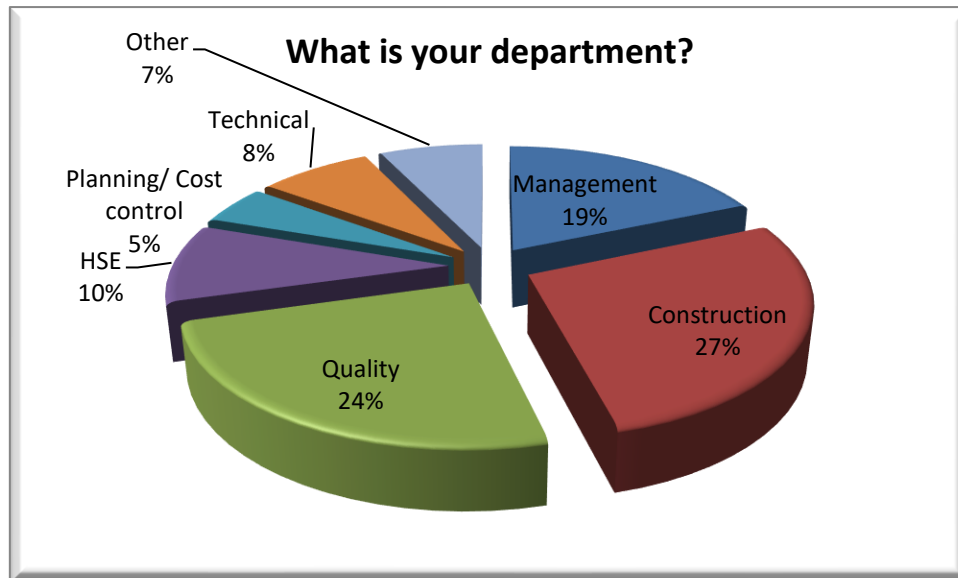
Table (4-3) Descriptive Analysis of Demographic Characteristics of the Study Sample			
Category		Freq.	Percent
experience do you have?	6 - 10 Years	38	22.8
	11 - 15 Years	53	31.7
	16 - 20 Years	28	16.8
	More than 20 years	36	21.6
What is your highest level of Education?	PhD	5	3.0
	Masters	64	38.3
	Bachelor	95	56.9
	Diploma	3	1.8
What is the scale of the project based on the budget?	Small < SR 50 million	17	10.2
	Meduim SR 50 - 200 million	36	21.6
	Big > SR 200 million	114	68.3
What is the scale and complexity of the project team	Small team (Less than 50 members)	26	15.6
	Meduim team (50-150 members)	37	22.2
	Large team (150+ members)	11	6.6
	Large multinational team (150+ members)	93	55.7
Did you acquire any of the following certificates?	PMP	97	37.3
	RMP	29	11.2
	Prince	4	1.5
	ISO Lead Auditor	49	18.8
	Lean Six Sigma	29	11.2
	Certified Manager of Quality	17	6.5
	Other	35	13.5
What is your gender?	Male	155	92.8
	Female	12	7.2

The table presents a descriptive analysis of the demographic characteristics of the study sample, showing the frequency and percentage of respondents in each category. The following observations can be made:

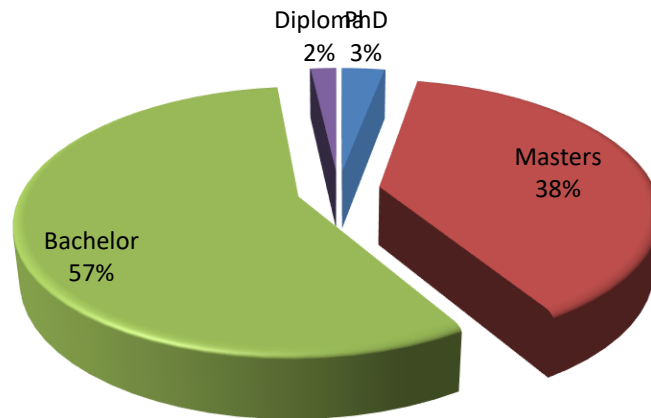
- **Role in the Company** The highest representation was for Senior Engineers at 31.2%, with 49 respondents, the lowest representation was for Inspectors at 3.8%, with 6 respondents.
- **Department** The Construction department had the highest representation at 27.5%, with 46 respondents m, the Planning/Cost Control department had the lowest representation at 4.8%, with 8 respondents.
- **Role of the Organization in the Project** The highest representation was for PMO/PMC at 31.1%, with 52 respondents. the lowest representation was for Suppliers at 1.8%, with 3 respondents.

- **Years of Experience** The highest category was 11–15 years of experience at 31.7%, with 53 respondents, The lowest category was 0–5 years of experience at 7.2%, with 12 respondents.
- **Highest Level of Education** The highest representation was for bachelor's degree holders at 56.9%, with 95 respondents, the lowest representation was for Diploma holders at 1.8%, with 3 respondents.
- **Project Scale Based on Budget** The largest representation was for large projects (> SR 200 million) at 68.3%, with 114 projects, the smallest representation was for small projects (< SR 50 million) at 10.2%, with 17 projects.
- **Project Team Scale and Complexity** The highest representation was for large multinational teams (150+ members) at 55.7%, with 93 respondents, the lowest representation was for large teams (150+ members) at 6.6%, with 11 respondents.
- **Certificates Acquired** The highest representation was for PMP certificate holders at 37.3%, with 97 respondents, the lowest representation was for Prince certificate holders at 1.5%, with 4 respondents.
- **Gender** The highest representation was for males at 92.8%, with 155 respondents, the lowest representation was for females at 7.2%, with 12 respondents.

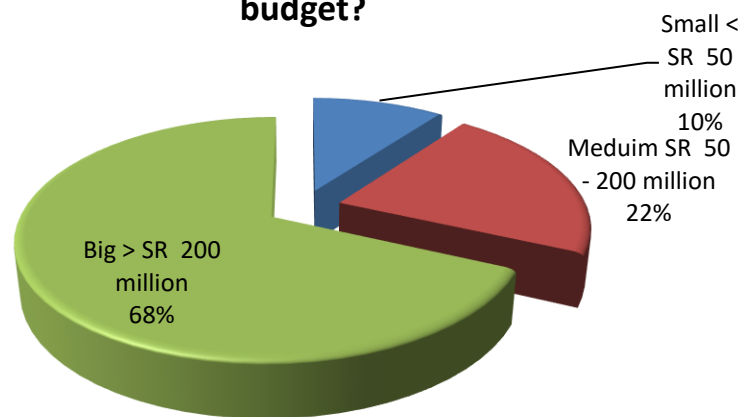




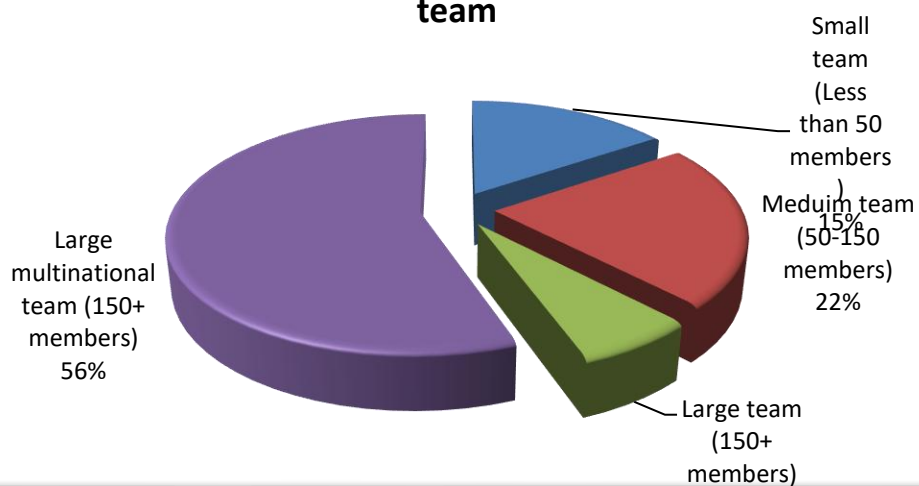
What is your highest level of Education?



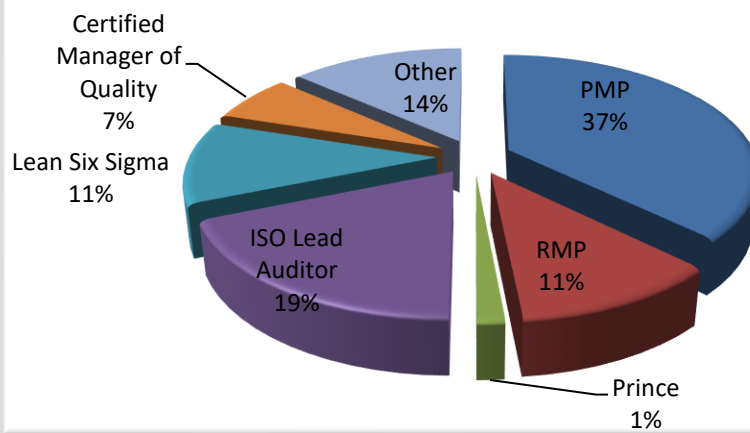
What is the scale of the project based on the budget?



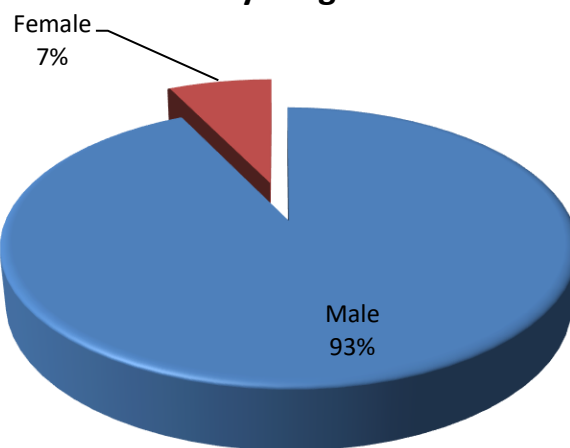
What is the scale and complexity of the project team



Did you acquire any of the following certificates?



What is your gender?



4.2.3 Open-ended questions Related to part A – Project Management Background & Experience

Table (4-4) Responses to the Question (Did you acquire any of the following certificates?) (Other (please specify))
Responses
Approval from client specially for inspectors
Building concertation specialist KUL K (Swe RISE)
Certified protection professional from ASIS
CLAC
Consultancy
Digital Transformation in Construction and Engineering Projects n
FMP
Grc
GRC
GRCP, GRCA, CCQM, CQA, CISSP, CISA
Igc
IOSH
IPMA D
ISO 9001 TO 2015 CERTIFIED
MPM
Nebosh
NEBOSH IGC
Non
Ongoing study for ISO Lead Auditor
OSHA
OSHA, NEBOSH
PCQM
Pgmp, PfMP
PMI-SP
PMOCP
PMS (Performance Management System audit)
Primavara
Quality assurance of concrete
Resolving project disputes
SCE
Value engineer
Safe
None

The table (4-5) presents respondents from JSWP projects

Table (4-5) Responses to the Question (If working on the Jeddah stormwater program include the project name for analysis purposes?)
Responses
AFAH
AL FIRDOUS
Al Hamdaniya
AL-Falah and AL-Hijaz
Albasteen
Alhamra project
Alsawari
Aproq alrogham
Client Representative as PMO
Drainage Solutions for Al-Hamdaniya District
I am working on other area at consultants office for facility management
Jeddah Storm Water Program
JSWP
N/A
None
Northern Channel Project
old makkah rd
PMCM
PMO in 2018 under WorleyParsons
PMO Team
Rawdah
SOUTH OBHUR
south projects
South ubher
storm drainage project Almarwah
SWRI & YAQT
WSP - all projects in the program of JSWP
Management and Supervision Office Consultant
Supervision of Stormwater Drainage Network Maintenance Projects
Al-Ruban, Al-Hamdaniah, Al-Falah, Al-Hijaz, Al-Salhiah, Al-Rahmaniah, Taybah
Al-Sawari, Al-Yaqout, KFRD, South Obhur
Al-Firdous
Previous Experience: Yes, Riyadh
All Stormwater Drainage Projects Under Implementation
Al-Firdous Project
Northern Canal Project
Stormwater Maintenance Project
Diriyah

4.2.4 Construction Quality Management subjects

Table (4-6): Distribution of the study subjects according to Construction Quality Management “CQM”				
Construction Quality Management “CQM”	Min- Max	Mean $\pm$ SD	median	Mean score percent
Quality is considered a core value within my organization and supported by higher management	1-5	4.26 $\pm$ 0.88	4.00	85.15%
Organizations’ Quality cultural patterns, like rituals, beliefs, values, and everyday procedures, directly or indirectly affect CQM practice?	1-5	4.12 $\pm$ 0.79	4.00	82.41%
ISO 9001 certification among stakeholders positively contributes to orgnasational and projects sucess	1-5	3.99 $\pm$ 0.84	4.00	79.76%
Difficulty in identifying quality defects at early stages	1-5	3.54 $\pm$ 1.00	4.00	70.90%
Challenges in managing and tracking defect resolution	1-5	3.59 $\pm$ 0.98	4.00	71.76%
Difficulty ensuring compliance with standards/specifications	1-5	3.47 $\pm$ 1.12	4.00	69.45%
Ineffectiveness in implementing corrective actions	1-5	3.17 $\pm$ 1.11	3.00	63.49%
Lack of structured preventive action mechanisms	1-5	3.44 $\pm$ 1.03	4.00	68.73%
Gaps in workforce skill level and training	1-5	3.86 $\pm$ 0.99	4.00	77.11%
Absence of standardized quality strategies or best practices	1-5	3.48 $\pm$ 1.09	4.00	69.52%
Spreadsheets (e.g., Excel)	2-5	4.28 $\pm$ 0.86	4.00	85.58%
KPIs Dashboards (Power BI / Tableau)	1-5	3.45 $\pm$ 1.21	4.00	68.90%
Generic project software (e.g., MS Project, Primavera)	1-5	3.21 $\pm$ 1.40	3.00	64.26%
Document-sharing platforms (e.g., SharePoint, Cloud storage, Google drive, Dropbox)	1-5	3.87 $\pm$ 1.18	4.00	77.38%
Enterprise software (e.g., Oracle Unifier, Procore, Aconex)	1-5	2.64 $\pm$ 1.50	3.00	52.85%
Quality Planning				
There is a formal Quality Management System with clear Quality objectives, policy, procedures, and KPIs within the organization	1-5	3.93 $\pm$ 0.86	4.00	78.68%
Project Quality Plans are prepared during the planning stage for each project	1-5	3.86 $\pm$ 0.91	4.00	77.13%
We use defined quality objectives, performance indicators, and checklists	1-5	3.81 $\pm$ 0.84	4.00	76.29%
Stakeholders are involved in the process of quality planning.	1-5	3.49 $\pm$ 1.01	4.00	69.70%
Lessons learned from previous / similar projects are used	1-5	3.49 $\pm$ 1.06	4.00	69.82%
Risk-based thinking is applied during quality planning to anticipate potential quality issues	1-5	3.49 $\pm$ 0.96	4.00	69.76%
Quality planning includes clear roles, responsibilities, and communication plans	1-5	3.71 $\pm$ 0.90	4.00	74.22%
Quality Assurance				
Quality audits are conducted regularly and effectively	1-5	3.86 $\pm$ 0.87	4.00	77.13%
Management review meetings are conducted regularly and effectively	1-5	3.72 $\pm$ 0.93	4.00	74.30%
Audit results are documented, communicated, and followed up with corrective or preventive actions	1-5	3.81 $\pm$ 0.80	4.00	76.29%
There are procedures to evaluate and control the quality performance of contractors, subcontractors, and suppliers	1-5	3.53 $\pm$ 1.00	4.00	70.66%
There are clear internal communication processes for enforcing quality standards	1-5	3.64 $\pm$ 0.95	4.00	72.89%
Top management demonstrates strong commitment to quality assurance	1-5	3.76 $\pm$ 0.97	4.00	75.15%
Quality Control				
There are a flow chart and procedures showing the process of quality control such as inspections, NCRs, SORs.	1-5	4.04 $\pm$ 0.87	4.00	80.72%
Regular inspections and testing procedures are followed as per ITP	1-5	3.99 $\pm$ 0.73	4.00	79.88%
Non-conformities are identified and corrected in a timely manner	1-5	3.66 $\pm$ 0.88	4.00	73.25%
Documentation systems (e.g., NCR logs, SORs, issue logs) are consistently used to track quality issues	1-5	3.96 $\pm$ 0.81	4.00	79.28%

Table (4-6): Distribution of the study subjects according to Construction Quality Management “CQM”

Construction Quality Management “CQM”	Min- Max	Mean $\pm$ SD	median	Mean score percent
Inspection and test results are reviewed and analyzed to identify trends and recurring issues	1-5	3.75 $\pm$ 0.84	4.00	75.09%
Coordination occurs between site engineers, QA/QC staff, and contractors to resolve quality issues	1-5	3.86 $\pm$ 0.83	4.00	77.13%
Quality Improvement				
Quality procedures are reviewed and updated regularly	1-5	3.80 $\pm$ 0.88	4.00	75.90%
There are effective mechanisms for capturing feedback and lessons learned	1-5	3.56 $\pm$ 0.95	4.00	71.27%
Training programs on quality standards are provided continuously	1-5	3.49 $\pm$ 0.99	4.00	69.70%
Corrective and preventive actions (CAPA) are actively implemented and monitored	1-5	3.65 $\pm$ 0.81	4.00	72.93%
Quality performance data is analyzed periodically to identify improvement opportunities	1-5	3.59 $\pm$ 0.93	4.00	71.81%

The table presenting the distribution of the study participants according to their Construction Quality Management “CQM” which were as follows:

- Items related to the importance of quality within the organization, support from top management, and the effect of organizational culture on CQM practices showed the highest means, ranging from 4.12 to 4.26 (82.41% - 85.15%).
- This indicates that participants recognize quality as a core organizational value and that a supportive culture effectively promotes quality management practices.
- Items regarding ISO 9001 certification recorded a mean of 3.99 (79.76%), reflecting participants’ acknowledgment of certifications’ role in enhancing project and organizational success.
- Items addressing difficulties in early defect detection, monitoring defect resolution, and ensuring compliance with standards showed means ranging from 3.17 to 3.59 (63.49% - 71.76%).
- These values suggest notable challenges in practical implementation of quality management, especially in corrective and preventive actions and defect resolution efficiency.
- The most significant challenge was ineffective implementation of corrective actions (3.17, 63.49%), indicating the need to strengthen follow-up and review mechanisms.

- Spreadsheet tools (e.g., Excel) recorded the highest mean of 4.28 (85.58%), reflecting a heavy reliance on traditional tools for quality tracking.
- Use of enterprise software was low (2.64, 52.85%), indicating limited adoption of integrated digital systems for quality management.
- This suggests a potential gap in digital transformation for modern quality management systems.

Quality Planning

- Items related to quality planning showed high means ranging from 3.49 to 3.93 (69.70% - 78.68%).
- This reflects the existence of formal quality management systems, clear objectives, KPIs, stakeholder involvement, and lessons learned from previous projects.
- Items with the lowest means were stakeholder involvement and lessons learned (3.49, ~69.7%), indicating potential for improving engagement and organizational learning.

Quality Assurance

- Means ranged from 3.53 to 3.86 (70.66% - 77.13%), emphasizing regular and effective audits, management reviews, documentation, and corrective action follow-up.
- The highest mean was for effective audits (3.86, 77.13%), while the lowest was for evaluating contractor performance (3.53, 70.66%).
- This indicates that quality assurance is generally effective, though monitoring of external parties could be strengthened.

Quality Control

- Items related to quality control showed high means ranging from 3.66 to 4.04 (73.25% - 80.72%).
- The highest mean was for flowcharts and procedures for QC processes (4.04, 80.72%), while the lowest was for timely correction of non-conformities (3.66, 73.25%).
- This reflects effective QC processes, with room to improve speed of issue resolution.

Quality Improvement

- Means ranged from 3.49 to 3.80 (69.70% - 75.90%).
- The highest mean was for regular review and updating of procedures (3.80, 75.90%), while the lowest was for continuous training programs (3.49, 69.70%).
- This indicates a strong focus on quality improvement, though there is a gap in continuous training to enhance workforce competence.

4.2.5 Open-ended questions for Part B – CQM Practices background

Table 4-7 below shows the response to Question 14 - used tools for CQM

Table (4-7) Responses to the Question (Which tool of the above mentioned do you find most effective, and why?)	
Responses	
Document-sharing platforms -Spreadsheets	
Aconex (easier familiar for our engineer)	
AI	
All are effectively useful	
all part of our daily works	
DOCUMENT SHARING PLATFORMS BECAUSE IT IS EASILY ACCESSABLE FOR EVERY ENG IN OUR PROJECT.	
Dropbox cause it has access for everyone	
Enterprise software can help in transforming the industry	
Excel & KPI & documents platform	
Excel & Primavera	
excel and power bi are the only avialbe and works good for us to follow up progress of works and make client reports	
Excel and sharepoint allow for easy sharing across multiple teams. Different teams use different enterprise software so sharing across multiple teams poses difficulties.	
First one , because i sometime used	
Generic project software. Because it's essential to build a project Baseline.	
In EHSS: Excel, power point, share point	
Kpi	
Microsoft Excel because everyone knows how to use it	
only excel is used to track ncr and sor and to make reports	
Oracle ,, the only available in our company	
Oracle is ver helpful as it can automate the proceses, help in centlize all the work flows and follow it up from the management	
Power BI helps in present the results of data analysis	
Power BI is excellent tool to resent project data with help from excel	
Primavera as it's integrates timeline, cost and resource, which very beneficial and gives clear picture of where projects are going.	
Primavera, KPI	
Primavera, since it provides clear charts that are automatically generated from schedules and progress updates.	
Primavera, since it's tracking the progress, and accordingly can track any delay due to quality issues.	
Share point : easy access + simple to use	
share point helps in keeping the data secure and cna be shared	
Shared folder to minimise communication for update	
SharePoint site for every project - due to the scaleability to Planner and former Projects MS and all the Micorsoft dynamics for 365.	
SharePoint, because of the integration with MS Office and the sharing permits and limitations for confidentiality.	
Sharepoint, MS Project, PrimaVera	

Table (4-7) Responses to the Question (Which tool of the above mentioned do you find most effective, and why?)	
Responses	
Sharing platforms	
Software and excel	
Spreadsheets (e.g., Excel). The most effective feature in Microsoft Excel is the PivotTable, because it allows users to quickly summarize, analyze, and explore large datasets without writing complex formulas. It's powerful, user-friendly, and ideal for extracting insights from raw data with just a few clicks.	
Spreadsheets & KPIs Dashboards	
spreadsheets since I can customize it for each project's unique challenges	
there is no modern software to otomize the works like Unifier	
Unifier, because it's a good and easy way to share + save data	
we only use excel, mangement does not want to pay for new technology	
Performance dashboards, unfortunately not utilized	
Performance indicator	
Collaboration platforms	
Aconex system for document management	

Table 4-8 below shows the response to Question 15 (Please describe any specific challenges faced in implementing or improving quality practices?)

Table (4-8) Responses to the Question (Please describe any specific challenges faced in implementing or improving quality practices?)	
Responses	
A key challenge in implementing or improving quality practices is resistance to change, as employees may be hesitant to adopt new processes. Other challenges include lack of management support, insufficient training, and unclear quality goals, all of which can hinder the success of quality initiatives.	
By focusing on quality assurance, every challenge on site can be faced properly	
Challenges related to cohesive quality checks and tracking of the effectiveness of the preventive actions.	
Challenges to quality could sometimes be affected because of not having enough time to finish an item, tho we must have the consultant agree to the new case of change. If it does the purpose and the same function and delivers the need of the item.	
Contractors' higher management refusing to co-operate.	
cooperation from all teams	
culture	
Delay of approvals from client side + stakeholders utilities clashes impact	
Having none skilled workers within the team	
I suggest to use Oracle it can help in spdd the work and minimise paper work waste	
Improper communication between team members	
it is hard to analysise and combine data from all project	
Lack of communication between the team Decisions made individually	
lack of follow up and improvement	
Lack of knowledge about quality procedures	
Lack of required skill among the employees	
lack of support from other teams especially construction.	
Lacking of training	
Learning & education & found the person who certified	
Lot of existing utilities on the mainline of storm drainage	
Majority of the team don't understand the importance of the quality and they don't have the required skills	
Management commitment to quality and to invest in new tools that might reduce the gap such as Aconex or Unifier	
mangement and cost of technology	
Mony	
NA	
Rushed deadlines	
Situations of current utilities and lack of as-built data are affecting excavation, installation and backfilling works	
So far nil	

Table (4-8) Responses to the Question (Please describe any specific challenges faced in implementing or improving quality practices?)

Responses
Some miss understanding by sites persons, green washing (trying to make data look excellent), no review for data before submission,
Subcontractor
Subcontractor management
support from construction manager to quality team
support is needed from other sections to get correct data
the absence of share folder or cloud service to store the data
the human willingness
The need of a defined platform for project management and CRM for one WSP (refer to Swedish market). My former background from finance and project management and market manager gives me the question of how we work with relationship management to expand on going businesses.
the quality of data produced from the team
The weakness of the management and the design institute.
There is no separate quality department in the company, which makes it hard to support the quality culture because it reports to the execution department. Only one quality engineer is working in the project, which is not enough because he handles both site and office work. The client asks to finish some lines quickly.
To train unskilled staff to use Qc measures and keep monitoring them to be on track
Too robust procedures, not able to put in place, concentrating in the main ones only.
Train unskilled staff to implement Qc measures and keep monitoring them
Unclear scope for contractors
urging workforce to adhere to quality compliance
we dont have support from project manager, he want progress and to save cost. many quality issues come from consultant because of his mentality
we want to use AI but the company policy does not allow it, we want mangement support to make our job easy
When the client/end user gets involved and have a deadline near to completion of the project, they influence a lot.
why still use of use of paper based reuquest
Wrong specification
Proactive measures and planning for them
Dealing with language differences
Collaboration from the execution team and support from the quality team
General concept of quality management among management and staff, without separating QA and QC concepts
Awareness
General awareness
Some subcontractors are poorly trained – lack of supervision team members for follow-up
Slight delay in management response to correct course
Repetition of the same observations at different sites
Standardization of platforms for procedures, especially with external parties like contractors
Support for the construction team from consultant and contractor is essential to achieve quality goals
Support for the quality department from management and other departments
Contractor refusal under the pretext of an emergency
Cybersecurity challenges in the facility – poor compliance in applying quality tools by some staff
Non-compliance with requirements despite the presence of basic compliance guidelines
Contractor non-compliance with quality
Lack of sufficient training for staff on quality principles and tools leads to ineffective implementation

Table (4-9) Distribution of the study subjects according to Artificial Intelligence

Artificial Intelligence	Min-Max	Mean $\pm$ SD	median	Mean score %
Awareness & Readiness				
I am interested in learning and using (AI) to enhance practices in my organization, including quality management	2-5	4.19 $\pm$ 0.75	4.00	83.71%
I personally use AI tools such as ChatGPT and similars, to improve my productivity	1-5	3.83 $\pm$ 0.91	4.00	76.53%
I am familiar with AI technologies (e.g., ML, NLP, computer vision, IoT)	1-5	3.08 $\pm$ 1.04	3.00	61.68%
There are initiatives in Our organization to integrate AI in project process including quality	1-5	3.18 $\pm$ 0.97	3.00	63.61%
Special training on using AI tools is needed for our staff	1-5	4.05 $\pm$ 0.96	4.00	80.96%
Staff are competent and open to using AI tools in quality management	1-5	3.35 $\pm$ 0.90	3.00	67.03%
The current system in your organization is ready to be integrated with AI technology	1-5	3.30 $\pm$ 0.88	3.00	66.02%
The integration of AI can positively influence the project's outcomes and overall success	1-5	3.80 $\pm$ 0.87	4.00	75.90%
AI Utilization				
AI tools can be used for generating quality requirements from historical data	1-5	4.03 $\pm$ 0.79	4.00	80.60%
AI Could help automating operations and digitalizing processes to improve productivity, safety, and quality	1-5	4.05 $\pm$ 0.76	4.00	81.08%
AI Integration can help analyze quality data and identify trends and patterns	1-5	4.05 $\pm$ 0.75	4.00	81.08%
AI Could help improve communication and collaboration between stakeholders on quality issues	1-5	3.83 $\pm$ 0.80	4.00	76.63%
AI supports compliance checking with codes, standards, and projects specifications	1-5	3.99 $\pm$ 0.82	4.00	79.88%
AI-powered dashboards are used for predictive insights during project execution	1-5	3.81 $\pm$ 0.87	4.00	76.24%
AI tools help in detecting errors or defects earlier than traditional methods, especially if integrated with dashboards	1-5	3.87 $\pm$ 0.83	4.00	77.37%
AI Integration help to predict and prevent errors related to humans, observations, non-conformities, before they occur	1-5	3.79 $\pm$ 0.84	4.00	75.81%
Challenges				
Our organization's top management is committed to exploring and supporting the use of AI	1-5	3.51 $\pm$ 0.88	4.00	70.18%
There is strong organizational interest in applying AI in all processes including quality	1-5	3.44 $\pm$ 0.90	4.00	68.74%
Implementation cost is a major concern that limits the adoption of AI	1-5	3.56 $\pm$ 0.87	4.00	71.26%
Our current systems and tools can be integrated with AI with minimal adjustments	1-5	3.37 $\pm$ 0.95	3.00	67.43%
There is a lack of internal AI-related training programs for staff	1-5	3.78 $\pm$ 0.91	4.00	75.57%
We face challenges in collecting and organizing quality-related	1-5	3.55 $\pm$ 0.92	4.00	71.02%

Table (4-9) Distribution of the study subjects according to Artificial Intelligence				
Artificial Intelligence	Min-Max	Mean $\pm$ SD	median	Mean score %
data that AI systems can use				
There are concerns about the accuracy and reliability of AI-generated quality insights	1-5	3.65 $\pm$ 0.81	4.00	73.05%
Our organization sees AI as a future enabler for improving overall project delivery	1-5	3.49 $\pm$ 0.83	3.00	69.82%
Current CQM workflow can be integrated with AI for better predictive control	1-5	3.53 $\pm$ 0.86	4.00	70.54%
We are actively exploring partnerships or solutions to enhance AI capabilities	1-5	3.37 $\pm$ 0.87	3.00	67.43%
Transparency, bias, reliability, accountability, ethical and legal considerations are biggest concerns for using AI	1-5	3.62 $\pm$ 0.81	4.00	72.34%

The table (4-9) above presents the distribution of the study participants according to their Artificial Intelligence which were as follows:

Awareness & Readiness

- Items related to interest in learning and using AI to enhance organizational practices, including the need for specialized training, showed high means ranging from 4.05 to 4.19 (80.96% - 83.71%).
- Items related to personal use of AI tools, staff competence, and readiness of the current system showed moderate means ranging from 3.30 to 3.83 (66.02% - 76.53%).
- Items concerning familiarity with advanced technologies such as Machine Learning (ML), Natural Language Processing (NLP), Internet of Things (IoT), and organizational initiatives for AI integration showed the lowest means between 3.08 and 3.18 (61.68% - 63.61%).

AI Utilization

- Means for items related to using AI tools for generating quality requirements, automating operations, analyzing data, and improving communication ranged from 3.79 to 4.05 (75.81% - 81.08%).
- The highest means were observed in automating operations and data analysis (4.05, 81.08%), indicating effective use of AI tools to support operational and analytical processes.
- The lowest mean was for predicting and preventing human-related errors before they occur (3.79, 75.81%), reflecting challenges in fully leveraging predictive integration capabilities.

AI Challenges

- Items related to organizational support, cost, training, data collection, and reliability of AI insights showed moderate means ranging from 3.37 to 3.78 (67.43% - 75.57%).
- The highest mean was for the lack of internal AI-related training programs (3.78, 75.57%), while the lowest means were related to integration of current systems and exploring partnerships to enhance AI capabilities (3.37, 67.43%).
- Ethical, legal, transparency, and bias considerations scored a mean of 3.62 (72.34%).

4.2.6 Open-ended questions for Part D – AI applications in CQM

Open-ended response to Question 27: Recommendation for developing and implementing AI solutions for CQM practices

Table (4-10): Responses to the Question (What recommendations would you give for developing and implementing AI solutions for CQM effectively?)	
Responses	
AI is already used in othe industry, it must be available for quality and safety	
Before the developing we should enhance the quality culture among our project team.	
Client should request contractor to show serious implantation for training their staff for AI courses	
construction works is still late to use this new technology, contractors still using old tools in site	
Currently systems and practices and tools must be updated to be able to integrate with AI tools, and this will need a lot of management support as I face a lot of resistance to change	
Eny kind of possible action for supporting and implementing the development for CQM is highly preferred.	
For effective AI implementation in Construction Quality Management (CQM), consider these key recommendations: 1.	
Giving training to the employees	
I dont use AI, the manahgent will not support it	
I suggested software to do the inspections using mobile app, but I heared alot of rejections! how we can use AI when we dont have the support of the managers? lot of staff do not know AI technology, they need many training	
I think AI can not work alone, each project has different challenges and AI will not understand that some solutions are not applicable to all	
i think ise of AI will need training and use of new technology	
I urge the organizations to start to prepare for AI use, currently the insight is not clear but getting involved will let the organization be ready for improvement and increase the awareness of the organziaiton and its workforce. So, to start getting involved with traning, and preparing the infrastructure for AI use is recommended.	
improve the current systems to be integrated	
improvement in current systems to help ai integrations	
Management on top level need to own and manage the implementation of AI to business use.	
managemnt suport is required to apply new technology	
More awareness needed to explain about AI benefits	
N/A	
new technology is not easy to use and need training and company to invest	

Table (4-10): Responses to the Question (What recommendations would you give for developing and implementing AI solutions for CQM effectively?)
Responses
Not relying on AI for everything related to CQM and using traditional methods when necessary.
oracle can make use of AI easy, but it is need support from top management
organization to start training the staff and to start investing in compliance with the infrastructure to adopt AI tools.
other industry fields are using AI, but in construction it is very late
So far nil
still not everyone use it and need some time to be availabel, only use chatgpt
still we use normal tools on daily works, AI need strong technology
support from mangament to use it across all departments and invest fund to do it
support is required from our top management, i try to make change but alone cannot do it
technology will need alot of support and invesment from mangement
the construction industry is still late in using new technology we still use excel files
the must be intrest from company mangement to use this new technology. I know it can help, but we need more interview of this new AI
the new technology can be benifit to mange many sites
the use of new technology will need time, money and support from mangement and everyone. and also need to improve the current system and workflow, we still use excel and only excel!
there is a need to support AI from management and it and other sections
this is complete technology and will be good for young generation
To stat step by step this use case needs infrastructure for data collection from field devices to human data entry which needs to be designed and implemented first
Training for O&M staff is required
Training should be provided to all the employees in order to know how to use AI effectively
User training, IA implementation verification.
using AI for daily work will require efforts and support from other teams and top management, it is need money investemt to setup AI systems
we dont have system, only excel. manager want to save money.
we face many issues with underground utilities, company must use technology to scan it maybe if AI can help
we still use excel files for quality work its not modern these tools cannot use AI and the files not updated and stored in computers not share folder or cloud
we use excel for dalily works, some vertions are not the same and this is make it harder to have good data quality. the AI system need good data
An assistant tool, not an effective tool for delivering outputs
Using Artificial Intelligence could help in inter-departmental integration and producing more accurate reports
Adoption of specific platforms and training
Training and support
Full support from top management
Difficult to implement in the construction environment due to management mindset focused only on profit without prioritizing quality and safety
Programs that help organize dates and track delays in real-time
Building a culture of innovation and digital transformation
Employee training
Training all staff in the organization on AI program operations and how to use them
AI technology will require time to be adopted in the construction sector as contractors and consultants find it difficult to change their working methods
Intensive courses
Anything beneficial

Open-ended response to Question 28: further insights from respondents

Table (4-11): Responses to the Question (Please share any observations, insights, thoughts or experiences where AI improved or could have improved project outcomes?)

Responses
AI must be implemented and added for improving project outcomes.
All details should be documented and As built records accuracy is highly required
Analyzing historical data using AI and preparing reports for the routine daily work will improve the overall project outcomes and will also save time and money
bot safety and quaity in construction need alot of support from mangement and be seperate from construction team to be able to do its job
construction industry still slow to use new technology
Define Clear Quality Goals 2.
Definitely, AI can participate in improving project outcomes, since AI is capable of collecting real-time data and analyzing a massive amount of data in a short time, with such ability, we can say AI can contribute to project outcomes positively.
I tried to use AI but policy of IT cannot use everything. the company must help us use it to make or work faster and better
In Quality, no, but AI potential to enhance data collection, forecast issues, retrieve historical data, and risk identification are very obvious.
In this early stage - we would be helped with AI for implement to business use.
it can help integrate the results from all departments
It improved my productivity a lot, so I am sure when integrating with all teams it will bring huge improvements
My staff always kept use AI measures for their job duties
N/A
Same quality issues hapen again, no training for sub contractors. the use of excel make it hard to use chatgpt
the company must spend money in starting new systems
The shortcut to improve the CQM is use AI in the right skills, right place and in the right time.
the use of AI will require help from all departments becuase it can combine the results from all of them, but to do that mangement must help and give strong support and start act
Time savings in document processes.
Used with BIM for work sequence coordination
Review / Familiarization
Integration with stakeholders is important to leverage intelligence
Support from management, employee training, and AI awareness
Artificial Intelligence does not replace humans but enhances efficiency, accuracy, and speed, supporting teams in achieving better project outcomes. The main recommendation is to start with simple, measurable applications and gradually expand based on results
Anything beneficial
Establish clear training plans for employees

Table (4-12): Distribution of the study subjects according to Project Outcomes				
Project Outcomes	Min- Max	Mean $\pm$ SD	median	Mean score percent
project cost				
Quality practices help in controlling project cost overruns by reducing reworks	1-5	4.10 $\pm$ 0.82	4.00	81.92%
Rework due to quality issues increases project costs	1-5	4.14 $\pm$ 0.89	4.00	82.77%
Cost-related risks due to poor quality are identified and mitigated proactively	1-5	3.73 $\pm$ 0.92	4.00	74.61%
The organization tracks and reports both direct quality costs and indirect costs related to quality	1-5	3.56 $\pm$ 0.92	4.00	71.14%
project schedule				
The presence of robust CQM practices can reduce the frequency of rework and schedule overruns	2-5	4.25 $\pm$ 0.61	4.00	84.91%
Quality-related delays (e.g., material rejection, repair, rework) are concerning in our project	1-5	3.91 $\pm$ 0.90	4.00	78.20%
Early detection and resolution of quality issues contributes to avoiding negative schedule disruptions	3-5	4.24 $\pm$ 0.62	4.00	84.79%
overall project quality				
Robust CQM practices help in improving the overall quality of works	2-5	4.29 $\pm$ 0.62	4.00	85.87%
Few defects are observed during project handover and included in the snag list	1-5	3.88 $\pm$ 0.81	4.00	77.60%
Project outputs comply with specifications and quality standards	2-5	4.01 $\pm$ 0.58	4.00	80.12%
Post-handover claims due to quality defects are minimal, as issues are addressed before final project handing over	1-5	3.81 $\pm$ 0.85	4.00	76.14%
customer satisfaction				
CQM practices help to improve the overall quality of work, therefore increasing customer satisfaction	1-5	4.19 $\pm$ 0.67	4.00	83.71%
Clients or end users express satisfaction with delivered quality	2-5	4.01 $\pm$ 0.65	4.00	80.12%
Quality management improves stakeholder communication and satisfaction	1-5	3.89 $\pm$ 0.83	4.00	77.84%
Customer feedback is regularly collected and used to improve project delivery and quality performance	1-5	3.74 $\pm$ 0.86	4.00	74.73%

The table 4-12 presenting the distribution of the study participants according to their Project Outcomes which were as follows:

Project Cost

- Items related to the impact of CQM practices on controlling project costs, reducing rework, and proactively identifying cost-related quality risks showed means ranging from 3.56 to 4.14 (71.14% - 82.77%).
- The highest mean was for the item addressing increased costs due to rework caused by quality issues (4.14, 82.77%), reflecting participants' awareness of the direct financial impact of quality.

- The lowest mean was for tracking and reporting both direct and indirect quality costs (3.56, 71.14%), indicating a gap in documenting and measuring quality-related costs.

Project Schedule

- Items concerning the effect of quality practices on reducing rework and schedule overruns showed high means ranging from 3.91 to 4.25 (78.20% - 84.91%).
- The highest mean was for the item addressing the ability of robust CQM practices to reduce schedule overruns (4.25, 84.91%).
- Early detection and resolution of quality issues also contributed to minimizing negative schedule disruptions (4.24, 84.79%).

Overall Project Quality

- Items related to improving overall work quality, compliance with specifications, and minimizing defects during handover showed means ranging from 3.81 to 4.29 (76.14% - 85.87%).
- The highest mean was for improving overall quality of work (4.29, 85.87%).
- The lowest mean was for minimizing post-handover claims (3.81, 76.14%), suggesting some issues may still need additional attention before final project delivery.

Customer Satisfaction

- Items related to improving customer satisfaction through quality, stakeholder communication, and using customer feedback showed means ranging from 3.74 to 4.19 (74.73% - 83.71%).
- The highest mean was for improving overall customer satisfaction through quality practices (4.19, 83.71%).
- The lowest mean was for collecting and using customer feedback to enhance project delivery and quality performance (3.74, 74.73%).

4.2.6 Descriptive Statistics of Variables

Table (4-13) Descriptive Statistics of Independent Variables - CQM				
Variables	Mean±SD	Skewness	Kurtosis	Mean score percent
Quality Planning	3.68±0.68	-0.62	0.37	73.64%
Quality Assurance	3.72±0.70	-0.42	0.05	74.46%
Quality Control	3.88±0.59	-0.89	2.09	77.56%
Quality Improvement	3.61±0.76	-0.67	0.17	72.19%
Construction Quality Management “CQM”	3.73±0.57	-0.43	0.27	74.55%

Table (4-13) shows Descriptive Statistics of Independent Variables (Construction Quality Management “CQM”) the following Quality Planning 3.68±0.68 Mean score percent 73.64%, Quality Assurance 3.72±0.70 Mean score percent 74.46%, Quality Control 3.88±0.59 Mean score percent 77.56%, Quality Improvement 3.61±0.76 Mean score percent 72.19%, Construction Quality Management “CQM” 3.73±0.57 Mean score percent 74.55%.

Table (4-14) Descriptive Statistics of Mediating Variables (Artificial Intelligence)				
Variables	Mean±SD	Skewness	Kurtosis	Mean score percent
Awareness & Readiness	3.60±0.53	0.05	0.34	71.93%
AI Utilization	3.93±0.62	-0.74	2.26	78.61%
Challenges	3.53±0.52	0.07	0.72	70.67%
Artificial Intelligence	3.67±0.46	-0.26	0.95	73.38%

Table (4-14) shows Descriptive Statistics of Mediating Variables (Artificial Intelligence) the following Awareness & Readiness 3.60±0.53 Mean score percent 71.93%, AI Utilization 3.93±0.62 Mean score percent 78.61%, Challenges 3.53±0.52 Mean score percent 70.67%, Artificial Intelligence 3.67±0.46 Mean score percent 73.38%.

Table (4-15) Descriptive Statistics of Dependent Variables (Project Outcomes)				
Variables	Mean±SD	Skewness	Kurtosis	Mean score percent
project cost	3.88±0.60	-0.55	0.35	77.58%
project schedule	4.13±0.50	-0.02	-0.45	82.63%
overall project quality	4.00±0.49	0.00	0.57	79.93%
customer satisfaction	3.96±0.57	-0.35	0.45	79.11%
Project Outcomes	3.98±0.43	-0.32	0.74	79.63%

Table (4-15) shows Descriptive Statistics of Dependent Variables (Project Outcomes) the following project cost 3.88±0.60 Mean score percent 77.58%, project schedule 4.13±0.50 Mean score percent 82.63%, overall project quality 4.00±0.49 Mean score percent 79.93%, customer satisfaction 3.96±0.57 Mean score percent 79.11%, Project Outcomes 3.98±0.43 Mean score percent 79.63%.

4.2.7 Correlation Matrix between Variables (Pearson Correlation)

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.

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

H1: There is a significant relationship between Construction Quality Management “CQM”, Project Outcomes, and Artificial Intelligence.

Table (4-16) Correlation Matrix between Variables Independent Variables (CQM), Mediating Variables (AI) and Dependent Variables (Project Outcomes)															
Variables		Quality Planning	Quality Assurance	Quality Control	Quality Improvement	Construction Quality Management “CQM”	Awareness & Readiness	AI Utilization	Challenges	Artificial Intelligence	project cost	project schedule	overall project quality	customer satisfaction	Project Outcomes
Quality Planning	r	1													
	p														
Quality Assurance	r	0.647**	1												
	p	0.000													
Quality Control	r	0.607**	0.550**	1											
	p	0.000	0.000												
Quality Improvement	r	0.589**	0.551**	0.672**	1										
	p	0.000	0.000	0.000											
Construction Quality Management “CQM”	r	0.869**	0.828**	0.828**	0.821**	1									
	p	0.000	0.000	0.000	0.000										
Awareness & Readiness	r	0.315**	0.285**	0.339**	0.314**	0.374**	1								
	p	0.000	0.000	0.000	0.000	0.000									
AI Utilization	r	0.211**	0.270**	0.227**	0.159*	0.263**	0.616**	1							
	p	0.006	0.000	0.003	0.040	0.001	0.000								

Challenges	r	0.275**	0.270**	0.323**	0.344**	0.358**	0.581**	0.488**	1						
	p	0.000	0.000	0.000	0.000	0.000	0.000	0.000							
Artificial Intelligence	r	0.315**	0.328**	0.353**	0.326**	0.394**	0.846**	0.828**	0.846**	1					
	p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000						
project cost	r	0.407**	0.363**	0.366**	0.366**	0.451**	0.281**	0.251**	0.366**	0.362**	1				
	p	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000					
project schedule	r	0.149	0.159*	0.108	-0.027	0.121	0.187*	0.192*	0.244**	0.250**	0.429**	1			
	p	0.055	0.040	0.166	0.726	0.118	0.016	0.013	0.002	0.001	0.000				
overall project quality	r	0.487**	0.494**	0.511**	0.440**	0.577**	0.266**	0.204**	0.385**	0.347**	0.551**	0.403**	1		
	p	0.000	0.000	0.000	0.000	0.000	0.001	0.008	0.000	0.000	0.000	0.000			
customer satisfaction	r	0.501**	0.487**	0.501**	0.520**	0.600**	0.335**	0.362**	0.373**	0.427**	0.499**	0.324**	0.599**	1	
	p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		
Project Outcomes	r	0.517**	0.500**	0.499**	0.453**	0.590**	0.351**	0.331**	0.446**	0.454**	0.824**	0.636**	0.824**	0.805**	1
	p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed). * Pearson correlation test															

The correlation matrix presents the relationships between independent variables (Construction Quality Management – CQM), mediating variables (Artificial Intelligence – AI), and dependent variables (Project Outcomes). The analysis of the Pearson correlation coefficients (r) and their significance (p -values) provides insights into the strength and direction of associations among the study variables.

- **Relationship between CQM dimensions and Artificial Intelligence**

The four dimensions of CQM—Quality Planning, Quality Assurance, Quality Control, and Quality Improvement—show statistically significant positive correlations with AI (ranging from 0.315 to 0.353, $p < 0.01$).

The composite CQM variable also demonstrates a stronger positive correlation with AI ($r = 0.394$, $p < 0.01$).

Interpretation: This indicates that higher levels of CQM practices are associated with greater awareness, utilization, and integration of AI tools within the organization. Effective quality management appears to foster the adoption of AI as a supporting tool.

- **Relationship between CQM and Project Outcomes**

All CQM dimensions are significantly and positively correlated with Project Outcomes, with coefficients ranging from $r = 0.453$ to $r = 0.517$ ($p < 0.01$), while the overall CQM variable shows a strong correlation with Project Outcomes ($r = 0.590$, $p < 0.01$).

Interpretation: Robust CQM practices contribute directly to enhanced project performance, including cost control, schedule adherence, overall quality, and customer satisfaction. The strongest association is observed with the overall CQM construct, highlighting its cumulative effect.

- **Relationship between AI and Project Outcomes**

The mediating variable, AI, also exhibits significant positive correlations with Project Outcomes ($r = 0.331$ to 0.351 , $p < 0.01$).

Interpretation: This suggests that the use of AI tools, awareness, and integration within project processes positively impact project performance. Although the correlations are moderate, they support the role of AI as an enhancing factor in achieving better project outcomes.

H2: There is a positive impact of Construction Quality Management “CQM” on Artificial Intelligence.

To test the main study Hypothesis H2, the researcher used simple linear regression analysis of the effect of Construction Quality Management “CQM” on Artificial Intelligence.

Table (4-17) Test of Construction Quality Management “CQM”effect on AI											
Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	5.57	5.57	0.394	0.156	2.47	0.32	30.397	0.000*	5.513	0.000*
Residual	165	30.21	0.18								
Total	166	35.78									
a. Dependent Variable: Artificial Intelligence											
b. Predictors: (Constant), Construction Quality Management “CQM”											
*A function at the level of significance less than (0.05)											

The results of the simple regression analysis presented in the table indicate that Construction Quality Management (CQM) has a statistically significant positive effect on the use of artificial intelligence. The correlation coefficient ($R = 0.394$) demonstrates a moderate and positive relationship between the two variables. Moreover, the coefficient of determination ($R^2 = 0.156$) shows that the regression model explains 15.6% of the variance in artificial intelligence use among the participating organizations, which is considered acceptable in social and field studies where multiple influencing factors are present.

The value of $F = 30.397$ with a significance level of $\text{Sig} = 0.000$ indicates that the regression model as a whole is statistically significant, and that the independent variable (CQM) contributes clearly to explaining the variance in the dependent variable (artificial intelligence). Additionally, the t-test result for the coefficient ($B1 = 0.32$), with $t = 5.513$ and $\text{Sig} = 0.000$, confirms that the effect of CQM on artificial intelligence is real and statistically significant, rather than occurring by chance.

The coefficient value ($B = 2.47$) further suggests that an improvement in CQM practices is associated with increased levels of artificial intelligence use, reflecting the enabling role of quality management practices in facilitating the effective adoption of AI technologies.

In summary:

The findings indicate that enhancing Construction Quality Management practices significantly contributes to improving the adoption and utilization of artificial intelligence in engineering projects, supporting the study's hypothesis and emphasizing the importance of CQM as an enabler of digital transformation in the construction sector.

To test the main study Hypothesis H2, the researcher used Multiple linear regression analysis of the effect of Construction Quality Management "CQM" on Artificial Intelligence

Table (4-18) Test of using Construction Quality Management "CQM" effect on Artificial Intelligence

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	2.878	0.189		15.263	0.000*	18.226	0.000*	9.95%	
	Quality Planning	0.215	0.050	0.315	4.269	0.000*				9.95%
2	(Constant)	2.701	0.203		13.329	0.000*	11.793	0.000*	12.57%	
	Quality Planning	0.121	0.065	0.178	1.856	0.065				9.95%
	Quality Assurance	0.140	0.063	0.213	2.219	0.028*				2.63%
3	(Constant)	2.420	0.234		10.351	0.000*	9.855	0.000*	15.35%	
	Quality Planning	0.057	0.070	0.084	0.816	0.416				9.95%
	Quality Assurance	0.101	0.065	0.154	1.570	0.118				2.63%
	Quality Control	0.170	0.074	0.217	2.314	0.022*				2.78%
4	(Constant)	2.430	0.234		10.377	0.000*	7.599	0.000*	15.80%	
	Quality Planning	0.044	0.072	0.064	0.613	0.541				9.95%
	Quality Assurance	0.091	0.066	0.138	1.382	0.169				2.63%
	Quality Control	0.136	0.082	0.174	1.649	0.101				2.78%
	Quality Improvement	0.059	0.064	0.096	0.925	0.356				0.44%
a. Dependent Variable: Artificial Intelligence										
*A function at the level of significance less than (0.05)										

The Multiple linear regression results presented in the table provide a comprehensive assessment of how the different dimensions of Construction Quality Management (CQM) contribute to explaining the variance in the utilization of artificial intelligence (AI). The results reveal a progressive improvement in model explanatory power as additional CQM dimensions are introduced, yet with varying levels of statistical significance.

Model 1: Quality Planning

The first model shows that Quality Planning alone explains 9.95% of the variance in AI utilization ($R^2 = 0.0995$). The dimension has a statistically significant positive effect ($\beta = 0.315$, $t = 4.269$, $\text{Sig} = 0.000$), indicating that organizations with stronger quality planning practices are more likely to adopt and utilize AI tools. This result aligns with the notion that structured planning helps create an environment conducive to digital transformation.

Model 2: Adding Quality Assurance

When Quality Assurance is added in Model 2, the explanatory power increases to 12.57%, indicating an incremental change of 2.63%. Quality Assurance shows a significant effect ($\beta = 0.213$, $t = 2.219$, $\text{Sig} = 0.028$), while the effect of Quality Planning becomes statistically non-significant ($\text{Sig} = 0.065$). This suggests that formalized assurance procedures—such as inspections, audits, and compliance protocols—play a more direct role in supporting the adoption of AI technologies than initial planning processes.

Model 3: Adding Quality Control

In Model 3, the introduction of Quality Control further enhances explanatory power to 15.35%, representing a notable additional 2.78% contribution. Quality Control emerges as a significant predictor ($\beta = 0.217$, $t = 2.314$, $\text{Sig} = 0.022$), suggesting that operational monitoring and on-site quality verification procedures foster practical opportunities for AI integration, particularly in areas such as defect detection, automation, and real-time monitoring.

Model 4: Adding Quality Improvement

Model 4 shows only a slight increase in explanatory power ($R^2 = 15.80\%$), adding merely 0.44%. The Quality Improvement dimension does not exhibit a significant effect (Sig = 0.356), and the other dimensions also lose statistical significance. This indicates that continuous improvement activities may not directly influence AI utilization, possibly because they involve longer-term strategic refinement rather than operational processes where AI tools are more commonly applied.

Overall Interpretation

The Multiple linear regression results indicate that the most influential CQM dimensions in predicting AI utilization are Quality Planning, Quality Assurance, and most notably Quality Control. These dimensions demonstrate their importance particularly in the early and mid-stages of model development, before losing significance upon full model integration.

The findings highlight that:

AI adoption is closely linked to operational and procedural quality mechanisms, particularly those embedded within Quality Assurance and Quality Control. Continuous improvement, despite being essential for organizational development, does not appear to directly stimulate the adoption of AI tools. The final model explains 15.80% of AI utilization, indicating that while CQM practices play a meaningful role, AI adoption is also influenced by additional factors outside the quality management system.

H3: There is a positive impact of Construction Quality Management “CQM” on Project Outcomes.

To test the main study Hypothesis H3, the researcher used simple linear regression analysis of the effect of Construction Quality Management “CQM” on Project Outcomes.

Table (4-19) Test of “CQM” effect on Project Outcomes

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	10.49	10.49	0.590	0.348	2.34	0.44	88.178	0.000*	9.390	0.000*
Residual	165	19.63	0.12								
Total	166	30.11									
a. Dependent Variable: Project Outcomes											
b. Predictors: (Constant), Construction Quality Management “CQM”											
*A function at the level of significance less than (0.05).											

The regression results presented in the table indicate a strong and statistically significant effect of Construction Quality Management (CQM) on project outcomes. The findings show that CQM serves as an important predictive variable that explains a considerable proportion of the variance in project performance.

The correlation coefficient ($R = 0.590$) reflects a strong positive relationship between CQM and project outcomes. Furthermore, the coefficient of determination ($R^2 = 0.348$) shows that 34.8% of the variance in project outcomes can be explained by the level of implementation of CQM practices. This is a relatively high explanatory power within management and engineering research and highlights the essential role of quality practices in enhancing project performance.

The F-test result ($F = 88.178$, $Sig = 0.000$) demonstrates that the overall regression model is statistically significant at a level less than (0.05), confirming the model’s validity for prediction. Similarly, the regression coefficient ($B1 = 0.44$) was statistically significant ($T = 9.390$, $Sig = 0.000$), indicating that improving CQM practices leads to a measurable enhancement in project outcomes, including cost, schedule, quality, and customer satisfaction.

Collectively, these results indicate that enhancing Construction Quality Management is a key driver for improving project outcomes, and that

investing in quality planning, assurance, control, and continuous improvement directly contributes to reducing deviations and increasing overall project success.

To test the main study Hypothesis H3, the researcher used Multiple linear regression analysis of the effect of Construction Quality Management “CQM” on Project Outcomes

Table (4-20) Test of Construction Quality Management “CQM” effect on Project Outcomes

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	2.792	0.156		17.889	0.000*	60.048	0.000*	26.68%	
	Quality Planning	0.323	0.042	0.517	7.749	0.000*				26.68%
2	(Constant)	2.575	0.165		15.634	0.000*	37.551	0.000*	31.41%	
	Quality Planning	0.208	0.053	0.332	3.911	0.000*				26.68%
	Quality Assurance	0.173	0.051	0.285	3.362	0.001*				4.73%
3	(Constant)	2.292	0.188		12.168	0.000*	28.964	0.000*	34.77%	
	Quality Planning	0.143	0.056	0.229	2.532	0.012*				26.68%
	Quality Assurance	0.134	0.052	0.221	2.567	0.011*				4.73%
	Quality Control	0.172	0.059	0.239	2.898	0.004*				3.36%
4	(Constant)	2.298	0.189		12.180	0.000*	21.848	0.000*	35.04%	
	Quality Planning	0.133	0.058	0.213	2.313	0.022*				26.68%
	Quality Assurance	0.126	0.053	0.208	2.379	0.019*				4.73%
	Quality Control	0.147	0.066	0.205	2.216	0.028*				3.36%
	Quality Improvement	0.042	0.051	0.075	0.822	0.412				0.27%
a. Dependent Variable: : Project Outcomes										
*A function at the level of significance less than (0.05).										

The results of the multiple linear regression analysis presented in the table indicate that the dimensions of Construction Quality Management (CQM) serve as important explanatory variables that effectively contribute to improving project outcomes. This is clearly reflected in the gradual increase in the explanatory power of the model with the addition of each quality dimension.

Model 1: Quality Planning

The results show that including only the Quality Planning dimension explains 26.68% of the variance in project outcomes, which is a relatively high explanatory level. The beta coefficient ($\beta = 0.517$) was statistically significant at $p < 0.05$, indicating that quality planning is the primary

driver that positively and directly affects project cost, schedule, work quality, and customer satisfaction.

Model 2: Adding Quality Assurance

With the addition of this dimension, the explanatory power of the model increased to 31.41%, with an additional 4.73%. Quality assurance appears to be an additional supportive and enhancing factor for project outcomes, as conducting regular audits and effectively managing reviews contributes to overall project performance.

Model 3: Adding Quality Control

When the Quality Control dimension was included, R^2 increased to 34.77%, with an additional explanatory contribution of 3.36%. The beta coefficients and statistical significance indicate that quality control—including inspections, testing, and monitoring non-conformities—is a critical element for managing execution quality, reducing errors and defects, and strengthening overall performance.

Model 4: Adding Quality Improvement

This dimension had the least impact among the four dimensions, as it was not statistically significant (Sig = 0.412) and contributed only 0.27% to the explained variance. This suggests that continuous improvement efforts may exist but are less mature or influential compared to the other dimensions, or their effectiveness may depend on a higher level of quality implementation within organizations.

General Conclusion

Overall, the results indicate that Quality Planning, Quality Assurance, and Quality Control are key dimensions with significant effects on improving project outcomes, while Quality Improvement has a weak and statistically insignificant effect. The gradual increase in R^2 reflects the strength of the model and its ability to explain a substantial portion of the variance in project outcomes, emphasizing the strategic value of implementing an integrated quality management system in construction projects.

H4: There is a positive impact of Artificial Intelligence on Project Outcomes.

To test the main study Hypothesis H4, the researcher used simple linear regression analysis of the effect of Artificial Intelligence on Project Outcomes

Table (4-21) Test of Artificial Intelligence effect on Project Outcomes

Model	df	Sum of Squares	Mean Square	(R)	(R2)	B	B1	F test		T test	
								F	Sig	T	Sig
Regression	1	6.20	6.20	0.454	0.206	2.46	0.42	42.746	0.000*	6.538	0.000*
Residual	165	23.92	0.15								
Total	166	30.11									
a. Dependent Variable: Project Outcomes											
b. Predictors: (Constant), Artificial Intelligence											
*A function at the level of significance less than (0.05).											

The regression results presented in the table indicate that Artificial Intelligence (AI) usage represents an important predictive variable for improving project outcomes. The model shows a positive and statistically significant relationship between AI and project outcomes, with a correlation coefficient of ($R = 0.454$), indicating a moderate to strong association between AI adoption and better project results.

The coefficient of determination ($R^2 = 0.206$) shows that approximately 20.6% of the variance in project outcomes can be explained by the level of AI adoption. This highlights that leveraging AI can enhance project efficiency and help achieve objectives related to cost, schedule, quality, and customer satisfaction.

The F-test ($F = 42.746$, $Sig = 0.000$) confirms that the overall regression model is statistically significant at a level less than 0.05, validating the model's ability to predict project outcomes based on AI usage. Similarly, the regression coefficient ($B1 = 0.42$) was statistically significant ($T = 6.538$, $Sig = 0.000$), indicating that increasing AI adoption leads to tangible improvements in project performance.

These findings suggest that AI serves as a strategic tool for enhancing project performance by improving decision-making processes, data analysis, predictive accuracy, and stakeholder communication, which collectively positively influence various project outcomes.

To test the main study Hypothesis H4, the researcher used Multiple linear regression analysis of the effect of Artificial Intelligence on Project Outcomes

Table (4-22) Test of Artificial Intelligence effect on Project Outcomes

Coefficient ^a										
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R square	R square change
		B	Std. Error	Beta						
1	(Constant)	2.961	0.214		13.819	0.000*	23.162	0.000*	12.31%	
	Awareness & Readiness	0.284	0.059	0.351	4.813	0.000*				12.31%
2	(Constant)	2.796	0.227		12.295	0.000*	13.837	0.000*	14.44%	
	Awareness & Readiness	0.191	0.074	0.237	2.580	0.011*				12.31%
	AI Utilization	0.126	0.063	0.185	2.020	0.045*				2.13%
3	(Constant)	2.446	0.235		10.394	0.000*	15.262	0.000*	21.93%	
	Awareness & Readiness	0.066	0.078	0.082	0.849	0.397				12.31%
	AI Utilization	0.077	0.061	0.113	1.261	0.209				2.13%
	Challenges	0.282	0.071	0.343	3.955	0.000*				7.49%
a. Dependent Variable: Project Outcomes										
*A function at the level of significance less than (0.05).										

The results of the hierarchical regression analysis indicate that the dimensions of Artificial Intelligence (AI) affect project outcomes to varying degrees. Three main dimensions were examined: Awareness & Readiness, AI Utilization, and Challenges related to adoption and implementation.

Model 1: Awareness & Readiness

When only the Awareness & Readiness dimension was included, the model explained 12.31% of the variance in project outcomes. The regression coefficient was statistically significant ($\beta = 0.351$, $t = 4.813$, $\text{Sig} = 0.000$), indicating that individual preparedness and awareness of AI are key factors that support overall project performance improvement.

Model 2: Adding AI Utilization

With the addition of the AI Utilization dimension, the explanatory power of the model increased to 14.44%, with an incremental contribution of 2.13%. Both Awareness & Readiness and AI Utilization were statistically significant, showing that the actual use of AI tools complements and enhances the effect of awareness and readiness on improving project outcomes.

Model 3: Adding Challenges

When the Challenges dimension was added, the explained variance rose to 21.93%, with a substantial incremental contribution of 7.49%. The regression coefficient for Challenges was statistically significant ($\beta = 0.343$, $t = 3.955$, $\text{Sig} = 0.000$), indicating that overcoming organizational and technical obstacles is critical for maximizing the effect of AI on project outcomes, as these challenges may limit the ability of individuals to fully benefit from AI technologies.

General Conclusion

Overall, the results indicate that Awareness & Readiness, AI Utilization, and addressing Challenges are essential dimensions that collectively influence project outcomes. The hierarchical model shows that overcoming challenges becomes the most influential factor after accounting for the other dimensions, emphasizing the importance of combining training, effective tool use, and obstacle management to achieve maximum benefits from AI in enhancing project performance.

H5: The significant impact of Construction Quality Management “CQM” on Project Outcomes increases when mediated Artificial Intelligence.

Table (4-23): Testing the Mediating Role of Artificial Intelligence on the Relationship between CQM and

Coefficient ^a									
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	F	Sig.	R	R square
	B	Std. Error	Beta						
(Constant)	1.754	0.226		7.753	0.000*	37.318	0.000*	0.638	40.72%
Construction Quality Management “CQM”	0.361	0.049	0.484	7.346	0.000*				
Artificial Intelligence	0.239	0.060	0.260	3.966	0.000*				
Interaction	0.013	0.024	0.034	0.559	0.577				
a. Dependent Variable: Project Outcomes									
*A function at the level of significance less than (0.05).									

The regression results presented in the table examine the mediating effect of Artificial Intelligence (AI) on the relationship between Construction Quality Management (CQM) and Project Outcomes.

The model shows a high explanatory power, with $R = 0.638$ and $R^2 = 40.72\%$, indicating that approximately 41% of the variance in project outcomes can be explained collectively by CQM and AI.

The coefficients for CQM ($\beta = 0.484$, $t = 7.346$, $\text{Sig} = 0.000$) and AI ($\beta = 0.260$, $t = 3.966$, $\text{Sig} = 0.000$) are both statistically significant, suggesting that both effective construction quality management practices and the application of AI independently contribute positively to improving project outcomes.

However, the interaction term ($\text{CQM} \times \text{AI}$) was not statistically significant ($\beta = 0.034$, $t = 0.559$, $\text{Sig} = 0.577$), indicating that, in this model, AI does not significantly moderate the relationship between CQM and project outcomes. This suggests that while AI enhances project performance directly, its presence does not significantly alter the strength of the effect of CQM on project outcomes.

In summary, the results highlight the strategic importance of implementing robust CQM practices alongside AI applications to enhance project performance. AI contributes independently to project success, but in this analysis, it does not serve as a moderating factor that amplifies the effect of CQM on project outcomes.

Statistical Techniques and Analysis Procedures

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.

4.3 Quantitative Data Analysis

The qualitative phase of this study aimed to complement quantitative data and results by exploring the underlying mechanisms of how AI influences CQM and project outcomes withing JSWP. Beyond statical relationships, the intention was to understand how engineers, managers, and construction teams experience quality process in practice, and why AI is perceived as either an enabler or challenge in real world project settings.

To be able to do it, open-ended questions responses were drawn from the survey and projects documents. Making triangulation of these data, helped to validate patterns identified quantitatively and to uncover practical insights regarding organizational behavior, top management and teams' discipline and data readiness of AI integration with CQM practices.

4.3.1 Data sources and Triangulation approach

Three complementary qualitative sources were used in this study. First, open ended survey responses were collected: out of 187 valid responses included narrative answers in which participants described their personal experiences with CQM practices, highlighted perceived obstacles and challenges, and shared their opinions about AI use. Second, operational logs within JSWP were examined, including project quality documents such as NCR/SOR logs, inspection logs, field reports, and audit reports, as it provides real evidence of quality issues and defects, closure times, and delays. Finally, the Minutes of Meetings (MOM) form regular meetings with contractors that present, discuss, and present key decisions of recurrent issues, and corrective actions.

A hybrid **inductive-deductive** thematic analysis was performed. Open coding was first applied to all textual data to identify recurring phrases and contextual patterns. These initial codes were then clustered into higher-order categories aligned with the stud's theoretical constructs, quality planning, control, assurance and improvement, with AI positioned as a moderator. Pattern-matching logic was used to test whether perceptions expressed in the survey were supported by evidence from logs and MOMs, enhancing internal validity through data triangulation

(Creswell & Plano Clark, 2022). The following sections will present the themes that were drawn from this analysis.

4.3.2 Theme 1 – Early detection and predictive controls

Respondents consistently highlighted the potential of AI to transform inspection from a reactive process into proactive, predictive system. Phrases such as “AI could warn us before a defect happen” and “pattern recognition across sites can prevent rework” were found.

Supporting evidence found on NCR logs as it shows repeated issues in excavation and backfilling activities, related to material approvals and testing on materials stockpiles, typically identified late in the execution phase. Using the pilot data exported to power BI, a simple text classification algorithm simulated using n8n agents flagged similar NCR categories across multiple zones, suggesting the feasibility of predictive controls.

MOMs also reinforced this observation related to materials, in all projects especially during starting stage, as the contractors were given the instructions and correct practice to stock the backfilling materials and the required testing as per ITPs. AI agents also flagged this as potential quality control concern as missing these instructions will result in materials nonconformity which were actually detected and raised as NCR in some projects.

Interpretation: the alignment among survey perception, NCR patterns, and MOM emphasis confirms strong evidence that AI can act as a predictive enabler in quality control. This validates the hypothesis of AI moderations on CQM practices and the link to project outcomes.

4.3.3 Theme 2 – Data readiness and system Integration

Another dominant theme concerned the maturity of data systems feeding AI tools. Survey participants frequently mentioned fragmented records keeping and inconsistent inspection and NCR/SOR formats, as well as the extensive use of low-quality scanned documents that AI cannot process. As example, some responses stated, “we have many reports but no unified database”. This response highlights a major concern that AI cannot learn from unorganized and coded readable data. Which is also

supported by responses highlighting the need to have enterprise platforms such as Unifier instead of only relying on Excel files as most reported.

The analysis of inspection and material logs confirmed this fragmentation as file naming differed by contractors, NCR categories were manually coded and different among projects and also missing forms data were common. Audits' findings also supported that in most contractors it was found that logs and forms were not updated (NCR, SOR, etc.). In order to perform proper analysis, the researcher had to clean, refine and re-code or unify the data used for analysis using the AI Agents, as well as the logs that were fed into Power BI

Interpretation: All three data sources converge on the necessity of establishing digital standardization and data governance frameworks. Without clean, structured and accessible datasets, AI's contribution and integration to CQM practices remains theoretical rather than operational. This concern can be addressed by the presence of software such as Unifier or Aconex to help transform and unify the data collection process and also the reporting process derived from this data. This finding reflect the literature on AI readiness in construction such as Alhumoud et al., 2024.

4.3.4 Theme 3 – Process Discipline and Management Commitment

The third theme concerns top management considerations and support for quality and new technology especially in the construction sector. Respondents comments emphasized that managerial commitment determines the effectiveness of AI technology, as some comments included “AI cannot replace site and human inspection”, another said “AI will not replace site follow-up”, while one raised a major concern “without leadership enforcement, dashboards are only decorations”.

NCR closure statics confirmed this dependency. The researcher developed QAQC dashboard using NCR/SOR logs to track closure through Power BI. The clear representation of closure time using dashboard helped to flag the closure issues to Quality Team, where AI model from historical data gave predictions for closers. Audit findings and MOMs also highlighted the delay in SOR/NCR closures and the need

for proper corrective and preventive actions to prevent reoccurrence of repeated issues.

Interpretation: AI enhances transparency and accountability but cannot substitute leadership discipline. Its moderating power arises from amplifying managerial visibility, turning data into useful and insightful management actions.

4.3.5 Theme 4 – Workforce Adaptation and Capacity Building

A recurring pattern observed, related to workforce readiness and generational attitudes toward AI, during the analysis of demographic questions section A, and AI readiness and awareness questions on section D of the survey. Younger engineers particularly those with 0 to 10 years of experience; showed noticeably higher optimism toward the use of AI personally and in the construction industry. The open ended responses also supported that as they emphasized AI's ability to "reduce human error/", "speed up inspection", "data analysis", and "decision-making".

In contrast, several respondents from the older generation (20+ years of experience) expressed concerns linked to technological disruption, job security, AI cant replace human judgment, and organizational resistance. Many of these participants highlighted fears of "losing control", "AI bias and reliability", "dependance on unreliable technology, and "lack of clear system and training".

This generational divide reinforces the broader theme identified across the dataset: AI is not solely a technical challenge but a human capital and cultural readiness also. Younger professionals generally see AI as an enabler, while more experienced professionals remain cautious or skeptical due to habit, legacy systems, and perceived risks.

Interpretation: Sustainable AI adoption depends on workforce competence and psychological readiness. The cultural shift from manual CQM practices to data driven AI supported practices represents a core moderation channel of AI between CQM and project outcomes.

4.3.6 Practical AI Trial

As part of the qualitative exploration, a preliminary pilot trial was initiated from the researcher to evaluate the feasibility of integrating AI-

driven analytics into the existing reporting and quality management workflows of JSWP. The purpose of this pilot is not to generate mature analytical outputs at this stage, but to test data readiness, assess workflow compatibility, assesses the gap in the current system, and understand the potential contribution of AI agents in supporting CQM practices. The digital environment within JSWP is currently fragmented: Excel sheets serve as the primary medium for collecting and issuing and tracing NCRs, SORs, test results, and inspection logs; OneDrive is used for file storage; and enterprise Microsoft tools such as Power BI and Azure are available but not fully utilized by and department. Importantly, **there is no unified or program-wide JSWP data model or consolidated log system**, which poses challenges for automation and AI-based analysis.

The pilot involved establishing an early-stage workflow where selected quality records (such as NCR/SOR trends, recurring defects, and inspection findings) were cleaned, structured, and connected to Power BI dashboards, which were then linked to an AI processing layer using automation tools such as AI agents. Initial tests indicated that data extraction and structuring can be automated to a considerable extent, and that AI agents are capable of identifying recurring issues, summarizing inspection patterns, and flagging anomalies. However, these outputs remain preliminary, as the reliability of AI-generated insights is highly dependent on the consistency, completeness, and standardization of the underlying data. The current environment characterized by fragmented reporting, uneven contractor documentation practices, and variability in supervision coverage, requires further refinement before real-time AI insights can be considered dependable especially without the presence of consolidated or program wide system.

These early observations align with themes emerging from quantitative and qualitative responses, particularly those related to organizational readiness, data quality, and technology adoption barriers. Younger engineers demonstrated strong optimism toward digital and AI tools, whereas older practitioners expressed concerns about system reliability and change management, reflecting a broader cultural divide that directly affects AI readiness.

While the pilot remains in a developmental stage and is not yet producing validated outputs, it provides initial evidence that AI-assisted tools could enhance quality reporting, early issue detection, and decision support. Full deployment, however, will require systematic improvements in data governance, development of a unified data gathering and reporting structure, and clearer program-level frameworks for the integration of AI technologies across JSWP.