

**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
CAPA	Corrective and Preventive Action
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
MOM	Minutes of Meetings
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 Three

Research Methodology

Overview

This chapter will outline and explain the research methodology employed in the study to provide clear understanding of the framework used. The research seeks to examine the relationship between Construction Quality Management practices and project outcomes, and how it is negatively affected by the complexity and scale of large infrastructure projects. Additionally, the study will investigate the moderating role of AI in enhancing the effectiveness of CQM practices to amplify the positive influence of CQM practices to overcome the effect of size and complexity of projects, and project outcomes

Using a convergent mixed method case study approach as explained by Creswell & Plano Clark (2017), the study will use both qualitative and quantitative data, collected in parallel. The collection method for the primary data (quantitative) involves a structured questionnaire that the researcher developed to align it with the context of the case study. The secondary data (Qualitative) includes historical documentation including records and related logs—and Minutes of Meetings (MOM) from both completed and ongoing JSWP projects, which provide valuable qualitative insight and real-world context to the analysis.

Finally, to ensure the validity and reliability of the instrument and findings, statistical techniques using SPSS will be employed for descriptive testing, and SmartPLS to analyze the relationship between the variables, especially the moderating one. This combined methodological strategy enables triangulation of findings and offers a perspective on how AI integration can strengthen quality management practices in infrastructure development

3.1 Research Design

At the foundation of this research lies a clear articulation of its philosophical stance, methodological approach, and data strategy, following the guidance of Creswell and Plano Clark (2017, pp. 96–97) for reporting mixed methods studies. Adopting a convergent parallel mixed-methods design, this study employs a case study core design to integrate quantitative data with qualitative insights. This approach, grounded in pragmatism, enables the selection of the most suitable methods to address the research questions, considering the research context and potential consequences. Also, it involves the concurrent collection and analysis of both quantitative and qualitative data, followed by a phase of integration where the findings are synthesized to formulate comprehensive interpretations.

Within this convergent mixed-method design, both quantitative and qualitative data are gathered and analyzed concurrently. This parallel approach aims to provide a more comprehensive understanding of the relationship between Construction Quality Management practices and their impact on project outcomes, while also examining how Artificial Intelligence can enhance this relationship. The mixed-methods approach allows for data diversification, which enhances the clarity and comprehensibility of the data by supporting numerical data with qualitative data (Gürsoy & Özpolat, 2020). Also, it is appropriate for addressing research questions that require both breadth (quantitative) and depth (qualitative) of understanding (Ivankova et al., 2005).

For the quantitative part, a survey, developed by the author, will be used to gather information and insights from infrastructure projects including JSWP, focusing on CQM components and AI integration within the projects. The questionnaire is specifically designed to capture quantitative metrics related to project performance, quality management practices, and the adoption of AI technologies.

The qualitative part involves a thorough review of project documentation, including quality reports, audits findings, and projects logs, to extract in-depth and thematic insights into the practical application of CQM practices. Both parts will be given equal priority, and the results will be brought together during interpretation using a partial triangulation

strategy, where selected qualitative themes will be used to support, contrast, or elaborate on the quantitative findings.

Figure 3.1 illustrates the Procedural Flowchart of the Convergent Mixed Methods Case Study Design, inspired by Creswell and Plano Clark. This diagram represents the study's methodological structure, showing how quantitative data (collected via a structured survey of engineers, contractors, and stakeholders involved in JSWP and other infrastructure projects) and qualitative data (gathered through analysis of historical records like NCRs, SORs, and project dashboards) are collected concurrently and analyzed independently. Integration occurs at the interpretation stage, using partial triangulation to compare and relate findings. The diagram clarifies the procedural steps and reinforces the embedded nature of mixed methods within the Jeddah Stormwater Program case, ensuring methodological transparency and coherence.

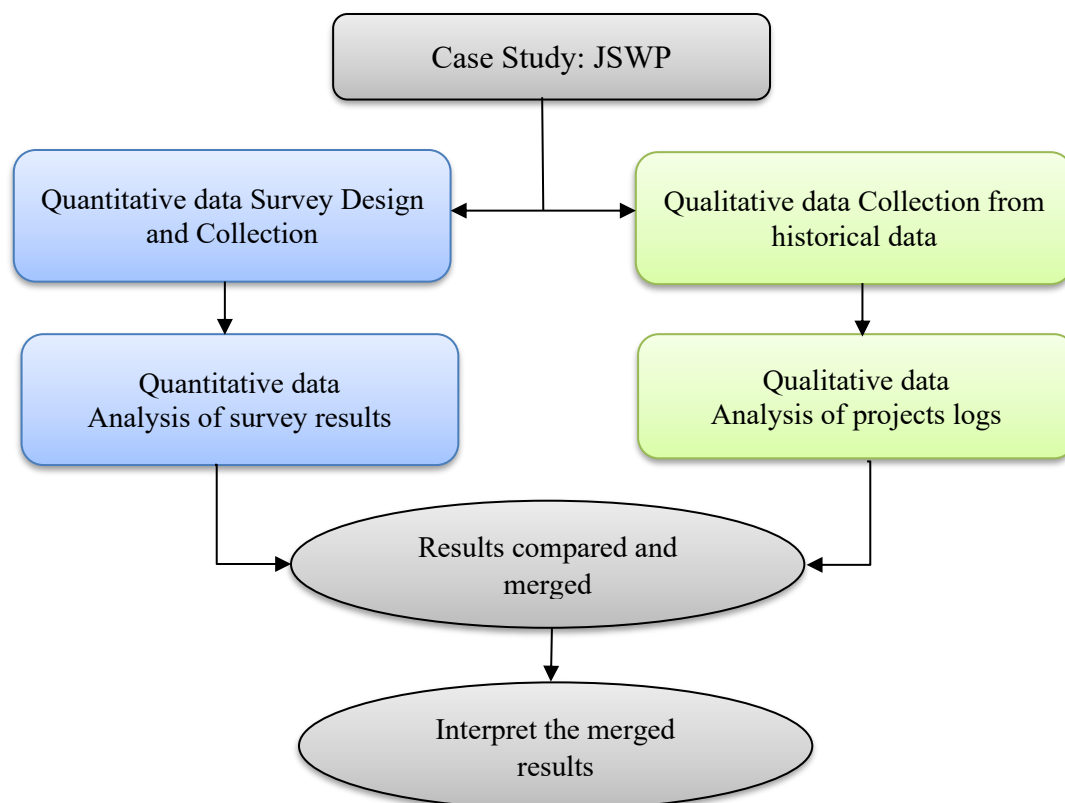


Figure 3.1: Procedural Flowchart of the Convergent Mixed Methods Case Study Design
Source: Inspired by Creswell and Plano Clark (2017, p. 119)

3.2 Justification for Mixed Methods

Quantitative researchers increasingly acknowledge the value of qualitative data in enriching and contextualizing their findings, while qualitative researchers recognize that relying solely on the views of a limited number of participants may restrict the generalizability of their results. The decision to adopt a mixed-methods approach is driven by the need to obtain a holistic and nuanced understanding of the intricate relationship between CQM, project outcomes, and the moderating effects of AI within the context of infrastructure projects. This is particularly important in the construction industry, where projects are diverse and complex, and AI technologies are rapidly evolving (Minc et al., 2022; Smajic et al., 2022).

Adopting a mixed methods design in this research is rooted in the premise that neither quantitative nor qualitative methods alone are sufficient to fully capture the complexity of issues inherent in large-scale construction projects (Ivankova et al., 2006). It also enables the collection and analysis of both qualitative and quantitative data, thereby providing a more comprehensive understanding of the research problem, by combining the generalizability of quantitative data with the contextual depth of qualitative insights.

The quantitative phase is conducted through structured surveys targeting key stakeholders within the infrastructure sector. The survey is designed to provide measurable insight into the perceived impact of CQM practices on project outcomes, highlighting the major challenges of current practices and the potential benefits of implementing AI applications. This will help to quantify the relationship between quality practices and project performance dimensions, including cost, time, quality, and client satisfaction.

The qualitative phase involves analyzing historical projects and quality records to explain, validate, and deepen the understanding of the survey findings. Drawing on the researcher's professional experience in quality management within the infrastructure sector, it is evident that while surveys provide valid perceptions, actual project logs reveal the root causes and operational realities behind quality failures. These records document real-world challenges observed during the execution of

infrastructure stormwater projects, offering detailed evidence of recurring issues, gaps in quality control, and systemic inefficiencies.

As a result, integrating quantitative and qualitative results enhances the robustness of findings, improving the interpretation of relationships between CQM, project outcomes, and AI technologies. This robust triangulation supports the development of a data-driven, AI-enhanced CQM model, aligning with Creswell and Plano Clark's convergent mixed-methods design to produce actionable, practice-informed conclusions.

3.3 Research Population and Sampling

The target sector for this research is the infrastructure construction segment within the Saudi construction industry. This focus is driven by the recurring issues in quality, coordination, and project outcome as discussed within previous Chapters, which are common in large-scale infrastructure projects, including JSWP. The unique challenges associated with these projects, such as their extensive scale, complex logistics, and significant public impact, make them a critical area for improving the traditional CQM practices. Furthermore, given the substantial investment in infrastructure development as part of Saudi Arabia's Vision 2030, enhancing CQM with AI in this sector holds significant economic, sustainability, and social value.

In alignment with this sectoral focus, the Jeddah Stormwater Program has been selected as the primary case study due to its complexity and scale as a key infrastructure initiative within the Kingdom, encompassing the entirety of Jeddah's master plan. The master plan comprising 92 projects across diverse disciplines, making JSWP a valuable representative of the infrastructure sector in the Western Region of Saudi Arabia. The program spans the entire city, adding another challenge due to the changing geology. Its multifaceted nature, involving numerous stakeholders, including 14 contractors, 20+ suppliers, and 3 consultants. In addition to the challenges it presents, and incidents from past rainy seasons and social impacts, the case provides a robust context for exploring CQM practices impact on project outcomes and the moderating role of Artificial Intelligence.

Given the program's complexity and its representative role in the infrastructure sector, a non-proportional stratified sampling strategy will be employed to ensure depth and relevance of insights. The target sample will include approximately 500 participants from infrastructure projects, particularly the Jeddah Stormwater Program (JSWP). Participants will be selected from distinct strata—such as engineers (including managers, supervisors, site engineers, and inspectors), contractors, subcontractors, consultants, suppliers. Unlike proportional sampling, this method will intentionally overrepresent certain strata, such as quality engineers and construction managers, to capture detailed information critical to the research focus on CQM, project outcomes, and AI integration. This stratified approach supports analytical richness and aligns with established research practices where specific subgroups are prioritized to better address the research objectives and hypotheses.

3.4 Instrumentation

Given the mixed-methods approach explained earlier in this chapter, this study employs two primary instruments to gather comprehensive data: a structured questionnaire for the quantitative phase and document analysis for the qualitative phase. The structured questionnaire is designed to collect quantifiable data from a broad sample of participants, enabling statistical analysis and the generalization of findings. Document analysis, on the other hand, involves in-depth review of project-related documents, such as quality control reports, meeting minutes, and progress updates, to provide rich, contextual insights that complement and validate the quantitative data obtained through the questionnaire.

3.4.1. Quantitative instrument

The research employed a structured, bilingual questionnaire (Arabic and English) as the primary data collection instrument for the quantitative phase of the mixed-methods design. The questionnaire was designed by the researcher to align it with the study objectives, drawing upon literature from Construction Quality Management, Artificial Intelligence integration, and project performance measurement frameworks. Its design was also informed by practical field experience within the Jeddah Stormwater Program (JSWP), ensuring contextual relevance. The survey instrument consists of four main sections.

Section A – Demographics and Project Background: Captures key demographic variables and contextual information such as role in the organization, department, type of stakeholder (client, consultant, contractor, etc.), years of experience, project size and complexity, educational background, and certifications. This section also includes identifiers for JSWP participants to enable contextual data analysis.

Section B – CQM Practices & Project Outcomes, consist of two parts: This section reflects the study's dependent variable and captures perceived effectiveness of quality planning, assurance, control, and improvement in driving project success. The first part assesses the current state of CQM practices, including presence of QMS, quality policies, procedures, KPIs, quality audits, and the influence of organizational quality culture. It also investigates the perceived benefits of ISO certification and the use of quality monitoring tools. While Part two of the section introduces Likert-Scale statements measuring the perceived impact of CQM practices on project outcomes.

Section C – AI Applications in Quality Management: The section helps to evaluate participants' awareness, interest, and perceived usefulness of AI technologies across three quality lifecycle stages: planning, execution (monitoring & control), and improvement. The statements explore the potential for AI in risk prediction, real-time quality monitoring, defect detection, automation, and decision-making.

Section D – Challenges, Concerns, Opportunities, and Future Vision for AI adoption in CQM: Through this section, open- and closed-ended questions regarding organizational readiness for AI, adoption barriers (cost, skills, data), and ethical/operational concerns will be investigated. It also explores stakeholders' perceptions of AI's future impact on quality management practices and their suggestions for successful implementation.

As explained above, the instrument integrates both closed and open-ended questions, facilitating triangulation by allowing statistical analysis of trends and qualitative insight into contextual challenges and opportunities. Questions were formulated to reflect constructs identified in the literature and structured to support the convergent mixed-methods approach (Creswell & Plano Clark, 2017). The 5-point Likert scale was

employed for attitudinal and perception-based items, allowing for meaningful quantification and subsequent statistical correlation between independent (CQM), dependent (project outcomes), and moderating (AI) variables. Prior to full deployment, the questionnaire will undergo expert review for content validity, and a pilot test will be conducted to assess reliability, clarity, and time efficiency. Revisions will be made accordingly.

3.4.2. Qualitative instrument

For the qualitative component, the study will analyze historical quality documentation, primarily NCR, SORs, Logs, MOM, and dashboards, all collected from completed and ongoing infrastructure projects within JSWP. These documents offer direct evidence of recurring quality issues, contractor performance, and procedural gaps, enabling deeper insight into the practical challenges of current CQM practices in large-scale infrastructure projects.

This document analysis complements the survey findings by providing context to statistical trends and uncovering underlying patterns not easily captured through questionnaires. The qualitative data will undergo thematic coding and categorization to identify key themes, including causes of non-compliance, effectiveness of quality interventions, CAPA and quality improvement efforts, and coordination challenges.

During the data analysis stage of qualitative data, AI tools such as Microsoft Azure will be utilized by integrating them into dashboards to enhance analytical capabilities. Historical NCR and SOR logs will be digitized and processed using predictive analytics and natural language processing (NLP) techniques to detect trends, classify issue categories, and forecast potential quality risks. Integrating AI within this phase supports the study's objective of developing a data-driven framework to strengthen Construction Quality Management (CQM) practices and improve project outcomes.

3.5 Validity and Reliability

Ensuring the validity and reliability of the research instruments and findings is critical to the credibility and generalizability of this study's outcomes to the broad infrastructure projects witting Saudi Arabia. Given the use of a mixed-methods convergent design, steps were taken to address both quantitative and qualitative standards of research rigor.

3.5.1 Quantitative Part

Content validity will be established through expert review. The questionnaire will be evaluated by academics in the fields of quality management and artificial intelligence, as well as practitioners from the Jeddah Stormwater Program (JSWP), to assess clarity, relevance, and alignment with the study's variables. Based on their feedback, necessary modifications will be made to enhance construct accuracy and eliminate ambiguities.

In addition to expert review, construct validity will be addressed by ensuring the final survey structure aligns with the theoretical framework discussed in Chapters 1 and 2. Each section of the questionnaire, as outlined in Section 3.4, will be mapped to specific research constructs to ensure conceptual coherence and measurement accuracy. The instrument will capture the four dimensions of Construction Quality Management (CQM)—quality planning, quality control, quality assurance, and quality improvement—alongside project outcomes (cost, time, quality, and stakeholder satisfaction) as the dependent variable. The moderating role of AI will be reflected in items measuring application level, awareness, perceived impact, and organizational readiness. To further assess convergent and discriminant validity, structural model testing will be conducted using SmartPLS.

Furthermore, face validity will be assessed through pilot testing with a small sample of 15–20 professionals representing the target population. Participants will evaluate the wording, structure, and usability of the questionnaire, and their feedback will guide revisions for clarity and reliability. Established measures for constructs such as CQM practices, project outcomes, and AI adoption will also be incorporated to strengthen validity (Mitra & Tan, 2012).

Finally, reliability will be examined using Cronbach's alpha to determine internal consistency of the Likert-scale items. A threshold of $\alpha \geq 0.70$ will be considered acceptable for each construct, in line with established guidelines. Items with low inter-item correlations will be reviewed and, if necessary, removed to improve scale reliability.

3.5.2 Qualitative Part

To ensure the dependability of the qualitative analysis, this study will apply a structured and replicable framework when reviewing and coding NCR and SOR logs, as well as meeting notes. Dependability, as described by Lincoln and Guba (1985), refers to the stability and consistency of research findings over time, ensuring that results are not arbitrary but are produced through a systematic process. This consideration is essential because the qualitative phase of this study involves large volumes of text-based data extracted from multiple projects within the Jeddah Stormwater Program (JSWP).

The analysis will follow a planned approach that includes the creation of a data extraction template to standardize the recording of relevant attributes, such as issue category, cause, project phase, and corrective actions. A coding manual will then be developed to provide explicit definitions of codes, inclusion and exclusion rules, and examples for clarity. Codes are expected to cover recurring themes such as material non-conformities, procedural deviations, inspection delays, and design-related errors.

The coding process will adopt an iterative strategy: an initial pilot test will be conducted on a small subset of logs to refine the coding scheme before applying it to the entire dataset. Comprehensive documentation will be maintained throughout the process to ensure auditability and transparency. In addition, where feasible, a subset of the data will undergo secondary review to validate the application of codes and enhance consistency.

3.6 Study Variables

The independent variable in this study is Construction Quality Management (CQM). CQM is measured through four established dimensions commonly adopted in construction quality frameworks: quality planning, quality control, quality assurance, and quality improvement. These dimensions collectively represent the formal practices, tools, and systems applied to ensure quality across the project lifecycle. Each of these sub-dimensions is addressed in the survey instrument using Likert-scale items that capture the extent of implementation and the perceived effectiveness of these practices in infrastructure projects, with a particular focus on the JSWP.

The dependent variable is Project Outcomes. This variable reflects the effectiveness and success of project delivery, measured through four key indicators: cost performance, schedule adherence, quality of delivered works, and stakeholder or client satisfaction. These indicators are widely recognized in construction and project management literature and serve as tangible outcomes influenced by the application of quality management practices. Data related to these outcomes are captured through respondent perceptions in the survey, enabling quantification of the relationship between quality inputs and project-level results.

The moderating variable is Artificial Intelligence (AI) Technology. AI is included to explore its potential influence on the strength or direction of the relationship between CQM and project outcomes. This variable is assessed through dimensions such as awareness and familiarity with AI tools, current and planned usage, perceived benefits, readiness for adoption, and key barriers to implementation. AI's moderating role is central to the study's hypothesis that technology, when integrated effectively, can enhance traditional quality management systems and improve construction project performance. This variable will also be contextualized using qualitative analysis of historical project data and digital quality logs, particularly where AI integration may support prediction or pattern recognition.

3.7 Data Collection Procedures

As the study follows a convergent mixed-methods case study design, where quantitative and qualitative data are collected during a similar timeframe, analyzed separately, and then merged for interpretation. The purpose of this design is to develop a comprehensive understanding of the impact of Construction Quality Management (CQM) on project outcomes and the moderating role of Artificial Intelligence (AI) within infrastructure projects, using JSWP as the case context.

3.7.1 Primary Data Collection

Primary data was obtained through a structured questionnaire distributed to stakeholders involved in infrastructure projects, with a primary focus on those working within JSWP. The questionnaire was administered digitally to ensure accessibility and higher response rates. Participants were selected using purposive sampling to ensure they have direct experience with quality management practices or AI-related initiatives. The survey instrument included items targeting the independent variable (CQM), the dependent variable (project outcomes), and the moderating variable (AI). A Likert-scale was used for quantification, and confidentiality of all participants was maintained. The data collection phase is designed to reflect diverse roles (e.g., engineers, managers, consultants, contractors) and project phases to capture a holistic view of the quality landscape.

3.7.2 Secondary Data Collection

To complement the primary dataset and support triangulation, qualitative data was collected from project documentation, particularly NCRs, SORs and MOMs. These documents were extracted from completed and ongoing projects under JSWP. The records span several project phases and involve multiple contractors and consultants, providing rich qualitative evidence of recurring quality issues, interventions, and outcomes. The documents were reviewed using a structured content analysis approach to identify key themes related to quality planning failures, procedural deviations, coordination inefficiencies, and supported by audits findings. This secondary data serves not only to contextualize the quantitative findings but also to identify patterns that may support the development of an AI-enhanced quality management framework.

3.7.3 Additional Qualitative Source: Meeting Minutes

In addition to formal documentation, this study incorporates insights from weekly quality coordination meetings, which served as an interactive forum for stakeholders to review project performance, discuss emerging quality challenges, and propose corrective measures. These sessions, involving consultants, contractors, and client representatives, are conceptually aligned with focus group methodology as they facilitate group dialogue and collective problem-solving. Meeting minutes and recorded discussions were systematically reviewed to extract themes related to CQM practices, recurring non-conformities, reoccurring and trending quality issues, and CAPA. These findings were later compared to survey data and document analysis for triangulation.

AI technologies (such as Microsoft Azure Machine Learning or Google Cloud AutoML) will be used in future phases to analyze patterns in the qualitative data and integrate them with dashboard metrics, enhancing and improving predictive capabilities and decision support. This integration reinforces the case study's applied nature and aligns with the convergent design by enabling data transformation, comparison, and synthesis.

3.7.4 Data Collection Matrix

Table 3.1 and Figure 3.2 provide a comprehensive overview of how this study aligns its research questions with the corresponding data sources, types of data, collection procedures, and analysis strategies. This mapping is an essential step in mixed-methods research design, particularly within a convergent approach, as it ensures methodological coherence and transparency. Each research question is addressed through multiple sources of evidence, combining quantitative survey data, qualitative document analysis, and contextual insights from weekly coordination meetings. For example, Research Question 1 focuses on the adequacy of CQM practices in large-scale projects, which is explored through structured questionnaires to capture stakeholder perceptions and through archival analysis of NCR and SOR logs to validate these perceptions against documented realities.

By presenting this alignment in both tabular and graphical formats, the study not only adheres to the best practices recommended by Creswell

and Plano Clark (2017) but also strengthens the validity of its mixed-methods design. The table serves as a structured summary, while the concept map (Figure 3.2) visually shows the logical connections between research questions, data sources, and analysis pathways, emphasizing the integrated nature of the research process.

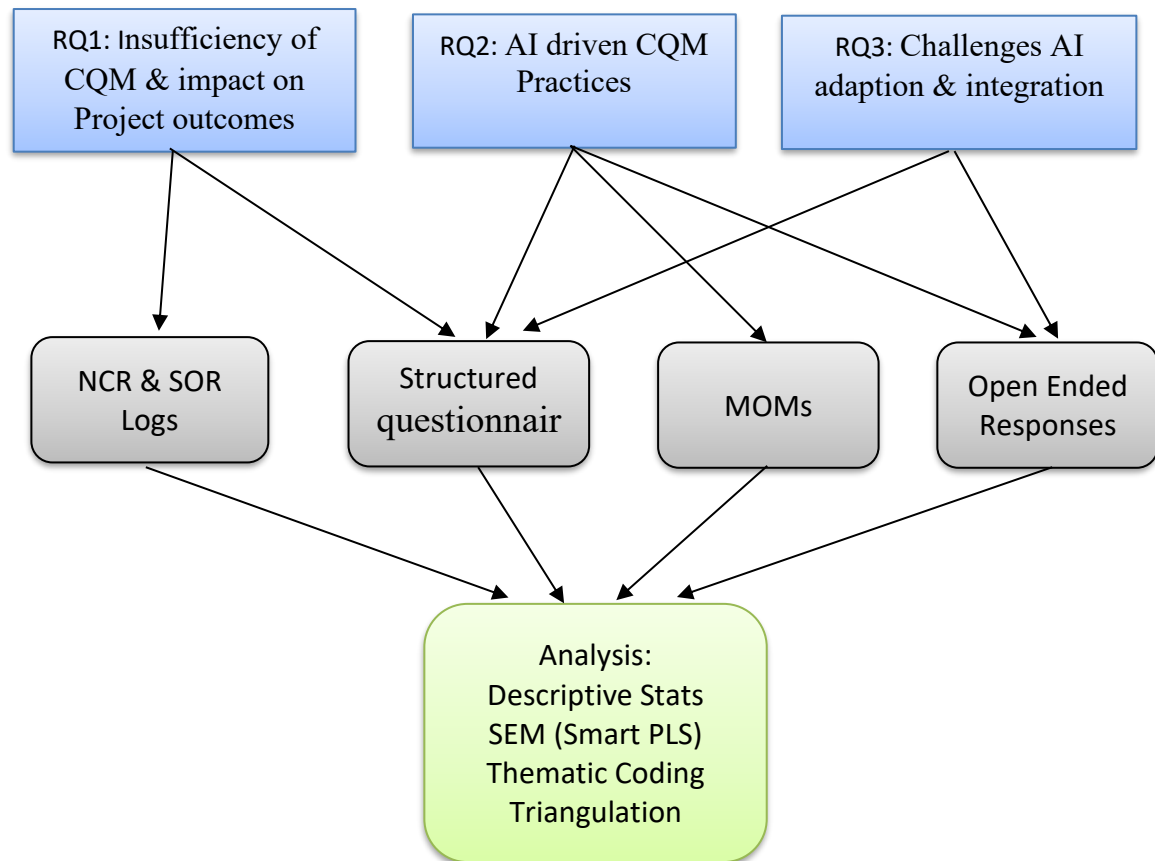


Figure 3.2: Concept map Linking Research Questions, Data Sources, and Analysis Methods
Source: Adapted from Creswell & Plano Clark, 2017

Research Question	Data Source	Type of Data	Collection Method	Analysis Approach
Research Q1: CQM insufficiency and its impact on project outcomes	Questionnaire Section B	Quantitative Likert scale, open question	Structured Questionnaire (Stakeholders)	Descriptive Statistics, SEM (SmartPLS)
	NCR & SOR Logs from JSWP Projects	Qualitative (Document Analysis)	Collection of archived documents	Thematic Analysis (CQM dimensions)
Research Q2: AI-driven CQM modifies impact of CQM on project outcomes	Questionnaire Sec. B & C	Quantitative	Structured Questionnaire	Moderation Analysis via SmartPLS
	Open-ended Responses		Documented meeting discussions	Thematic Analysis AI readiness & perceptions
Research Q3: Challenges for AI adoption and integration in CQM	Questionnaire Section D	Qualitative	Structured Questionnaire	Thematic Analysis (AI barriers)
	AI challenges and perception	Quantitative	MOM	Frequency Analysis
<i>Table 3.1: Data Collection Matrix aligned with research questions</i> <i>Source: Adapted from Creswell & Plano Clark, 2017</i>				

3.8 Data Analysis Methods

As explained earlier in this section, quantitative and qualitative datasets in this study are analyzed independently and merged during the interpretation phase. The aim was to enable triangulation, validation, and a comprehensive understanding of the relationship between CQM, project outcomes, and the moderating role of AI in large-scale infrastructure projects. The analysis is organized into three components: quantitative analysis, qualitative analysis, and data integration.

3.8.1 Quantitative Data Analysis

Quantitative data from the structured questionnaire will be analyzed using descriptive statistics to summarize respondent demographics and distribution across the main constructs: CQM, Project Outcomes, and AI. Following this, Structural Equation Modeling (SEM) will be employed using SmartPLS to assess relationships among variables and test

hypotheses, including moderation effects. SEM is appropriate for handling complex path models and reflective constructs, even with relatively small samples typical of case-based research. Reliability and validity will be examined through composite reliability, AVE, and discriminator validity. Respondents from contractor organizations will be asked to identify the specific JSWP project(s) they are involved in, enabling project-level linkage between survey responses and corresponding NCR/SOR data for deeper case-based analysis (Creswell & Plano Clark, 2017, p.72).

3.8.2 Qualitative Data Analysis

Qualitative data will be drawn from archival sources, primarily Non-Conformance Reports (NCRs) and Site Observation Reports (SORs) from completed and ongoing JSWP projects, supplemented by meeting notes and open-ended survey responses. A structured thematic content analysis will be employed, involving open coding, categorization, and theme development aligned with the CQM framework. Manual coding will be supported by AI-based Natural Language Processing (NLP) tools such as Microsoft Azure Cognitive Services to improve scalability and reduce bias by detecting patterns, clustering keywords, and forecasting quality risks. To ensure dependability, the analysis will follow a documented and replicable coding framework to maintain consistency. Themes related to AI readiness and adoption will also be extracted to complement quantitative findings (Creswell & Plano Clark, 2017, p.75).

3.8.3 Data Integration Strategy

After independent analysis, findings will be merged for triangulation to identify convergence, divergence, and complementarity between the two strands. Where feasible, qualitative themes will be transformed into frequency counts to support comparison, and joint displays will be developed to illustrate alignment between datasets. For instance, if a project shows high NCR rates in qualitative logs and corresponding survey responses report weak quality planning, this convergence will strengthen internal validity. Conversely, discrepancies will be interpreted in light of project complexity and organizational readiness for AI. The integrated insights will inform the development of an AI-enhanced CQM

model, supporting practical recommendations for improving quality performance in large-scale infrastructure programs.

3.9 AI Model Development Plan

As part of the future development phase of this research, an Artificial Intelligence (AI) model is planned to support and enhance Construction Quality Management (CQM) practices within infrastructure projects. This model is not being implemented at this stage but is intended as a conceptual and analytical extension based on the outcomes of the current study. The goal is to explore how AI can assist in identifying quality trends, predicting non-conformities, and improving decision-making processes based on historical project data.

The initial plan involves collecting and preparing existing data sources from completed projects, particularly those within the Jeddah Stormwater Program (JSWP). These include Non-Conformance Reports (NCRs), Site Observation Reports (SORs), project profiles, and performance dashboards. Additional insights will be derived from the survey data, particularly where participants discuss challenges and opportunities in applying AI to quality management.

To develop the AI model, cloud-based platforms such as Microsoft Azure or Google AutoML will be considered for their compatibility with real-time dashboards and analytics tools like Power BI. These platforms may enable integration with existing logs to allow for smarter classification, trend prediction, and real-time alerts.

Initially, AI applications may focus on Natural Language Processing (NLP) to analyze NCR and SOR text, identify recurring issues, and support theme extraction. Supervised learning models may later be explored to predict quality risks or detect early indicators of project non-compliance. The AI model will evolve based on the findings of the current research and data analysis and availability of AI applications.

This plan will be refined and updated after the completion of data collection and analysis phases. It represents a step toward integrating smart technologies into traditional quality frameworks and aligns with broader digital transformation goals within the Saudi infrastructure sector.

