

Exploring the Moderating Role of Artificial Intelligence on the Impact of Quality Management on Construction Project Outcomes

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the degree of Doctor of Philosophy in Management

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Problem Statement

Core problem observed on JSWP

- The Jeddah Stormwater Program involves multiple concurrent projects, contractors, interfaces, and changing site conditions, which strain traditional quality controls.
- Large, complex infrastructure programs such as the JSWP (89 similar projects) face persistent quality challenges: material defects, utility clashes, contractor non-compliance, rework, delays, cost overruns, and reduced stakeholder satisfaction.
- Traditional Construction Quality Management (CQM) is strained by project size, complexity, and the high volume of simultaneous activities.
- AI adoption in the Saudi construction sector lags global trends — despite Vision 2030's emphasis on infrastructure and digital transformation.

Research Questions

Research Gap

Limited empirical evidence on how AI influences (moderates) the effectiveness of Construction Quality Management practices on project outcomes.

RQ1

Does CQM become insufficient when project size and complexity increase, and how does this affect outcomes?

RQ2

Do AI-driven CQM practices modify the impact relationship between CQM and project outcomes?

RQ3

What financial, organizational, ethical and technical barriers affect AI integration into CQM?

Research Objectives



Main Objective

To examine how Construction Quality Management influences construction project outcomes and whether Artificial Intelligence strengthens this relationship in large infrastructure projects.

1. Evaluate traditional CQM limitations in complex infrastructure programs.

2. Test the effect of CQM dimensions on project outcomes

3. Assess AI as a potential moderator and operational enabler.

4. Identify barriers to AI adoption in construction quality governance.

5. Propose practical AI-integrated quality governance directions.

Study Significance

- ✓ **Theoretical contribution**

Provides empirical evidence linking CQM, AI, and project outcomes within a complex infrastructure case.

- ✓ **Practical contribution**

Guides contractors, consultants, and PMOs on digital quality governance and data-driven CAPA.

- ✓ **Policy/industry value**

Supports digital transformation in infrastructure delivery and aligns with Quality 4.0 thinking.

Study Significance

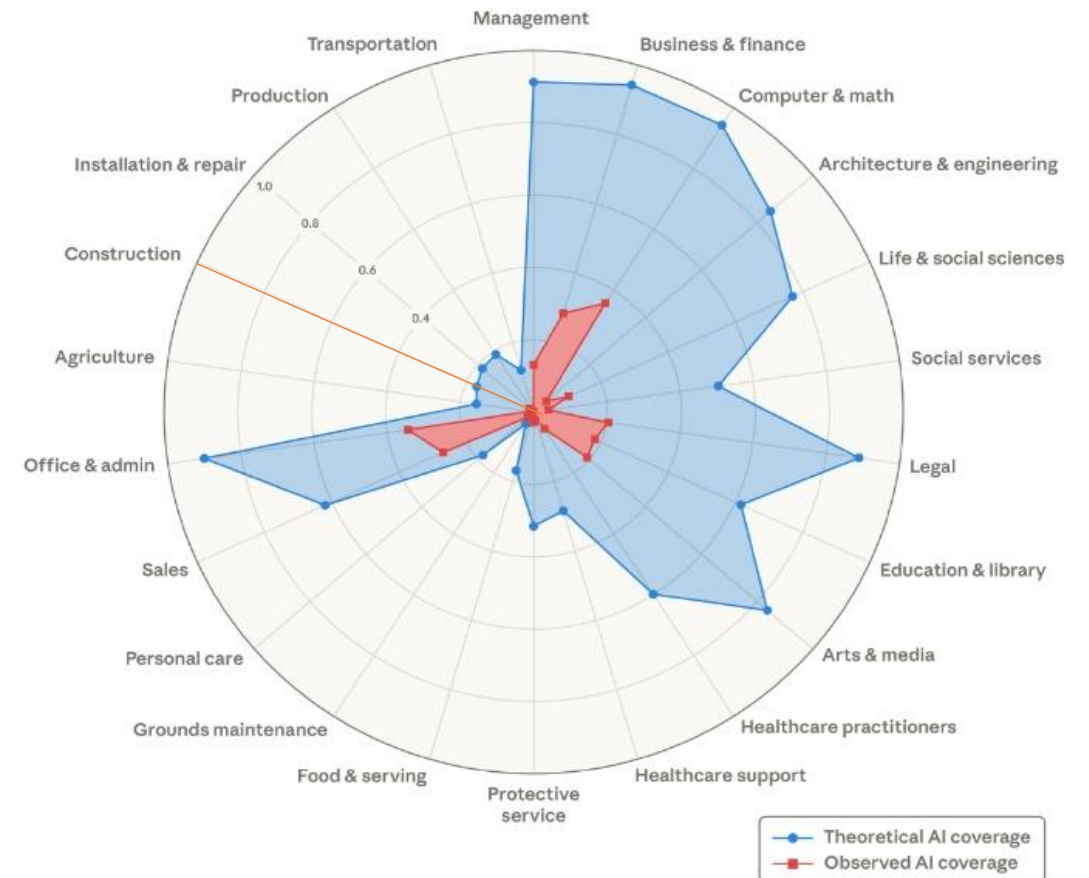
AI Adoption Gap in Construction

- The figure shows a clear gap between **AI's theoretical capabilities and observed usage** across occupations.
- Construction appears among the lowest observed AI-coverage categories, supporting the need to examine how AI can practically enhance CQM

Why it matters in construction quality management

- Quality deviations remain persistent even under formal QMS structures.
- AI may improve predictive monitoring, defect detection and decision support.
- The real challenge is moving from tool use to governed integration.

Theoretical capability and observed usage by occupational category



Source: Massenkoff & McCrory (2026), "Labor market impacts of AI: A new measure and early evidence," Anthropic, Figure 2.

Theoretical Framework

- **Foundation — Juran's Quality Trilogy, operationalized as four CQM dimensions (independent variable):**
 - Quality Planning · Quality Assurance · Quality Control · Quality Improvement
- Quality pioneers grounding the study: Deming (PDCA cycle), Juran (Trilogy), Crosby (Zero Defects), Feigenbaum (Total Quality Control), and Ishikawa (root-cause tools).
- **Project outcomes (dependent variable) measured by four universal indicators:**
 - Cost · Schedule (Time) · Quality · Customer Satisfaction

Theoretical Framework

Research Stream	Key References	Study Relevance
Construction Quality Management and project outcomes	Salvi & Kerkar (2020); Khan et al. (2019); Othman et al. (2018); Zakaria et al. (2017); Neyestani (2016); Low & Ong (2014); Hwang & Yang (2014);	Confirms CQM drives project outcomes (basis for H1) and that CQM is strained in large, complex projects
AI in construction and project management	Datta et al. (2024); Pan & Zhang (2021); Abioye et al. (2021); Makaula et al. (2021)	Establishes AI's broad potential but shows it rarely targets quality management — defining the research gap
AI and digital technology for construction quality	Dabous et al. (2023); Seyman-Güray (2023); Luo et al. (2022); Westenberger et al. (2021); Cubric (2020); Yang et al. (2019);	Closest prior work — AI enhances CQM but benefits are rarely tied to outcomes, and adoption barriers explain the transitional maturity (basis for H2/H3 and AI as moderator)
Saudi construction and AI adoption context	Hamdan (2024); Mazher et al. (2015); Aichouni et al. (2014); Assaf & Al-Hejji (2006);	Shows that Saudi construction faces recurring quality and performance challenges, including weak QMS implementation, limited training, management commitment gaps, delays, rework, and compliance-focused quality practices.

Methodology

Research Design

Research philosophy
Pragmatism

Design
Convergent mixed-methods
case study

Case
Jeddah Stormwater Program

Purpose
Statistical testing +
contextual triangulation

Data sources:

- **Quantitative:** structured questionnaire measuring CQM (4 dimensions), AI, and Project Outcomes on Likert scales.
- **Qualitative:** project records — NCRs, SORs, and 243 governance meeting records (11,000+ coded statements).
- **AI model input data** — NCR/SOR records, governance statements, quality warning indicators, and recurring issue categories.
- **Triangulation:** survey results, qualitative themes, and AI-assisted escalation outputs were integrated to support, contrast, and contextualize the quantitative findings.

Methodology

Study Population & Sample:

- **JSWP professionals / similar Projects:** project & quality managers, QA/QC teams, engineers, contractors, and suppliers.
- Purposive sampling; 167 survey responses collected, with ~130–140 valid observations used for SEM.

Data Analysis Tools:

Analysis software: IBM SPSS v25 and SmartPLS (Structural Equation Modeling):

- SPSS — robust for descriptive statistics, reliability testing, and regression analysis of observed (composite) variables.
- SmartPLS / SEM — models latent constructs and accounts for measurement error, estimating all structural paths simultaneously.
- SEM provides a more rigorous and conservative test of moderation than regression on observed scores — critical for a reliable conclusion on AI's interaction effect.

Key Findings

Key Findings

$$R = 0.590$$

CQM has strong positive correlation with project outcomes

$$R^2 = 34.8\%$$

CQM explains substantial variance in project outcomes

$$\beta = 0.451$$

SEM confirms direct CQM effect, $p < 0.001$

$$\beta = 0.017$$

AI moderation is not supported in SEM, $p = 0.448$

Interpretation

CQM remains a statistically significant foundation for improving project outcomes. AI shows value as a direct operational enhancer, but the tested SEM model does not support a mature structural moderating effect.

Hypotheses outcome

H1 supported:
CQM → Project Outcomes

H2 not supported under SEM:
AI × CQM

H3 supported conceptually: barriers
limit integration

Conclusion & Recommendations

Conclusion

The sector is transitioning toward AI-enhanced CQM. Current AI use improves monitoring and decision support, but it is not yet embedded enough to transform quality governance structurally.

Stage 0
Traditional CQM

›

Stage 1
AI-enhanced CQM

›

Stage 2
Integrated digital
governance

Recommendations

- 1 Establish executive digital quality governance.
- 2 Build AI competency programs for quality and project teams.
- 3 Integrate AI analytics into quality monitoring and reporting.
- 4 Reduce spreadsheet dependency through integrated platforms.
- 5 Strengthen CAPA using centralized NCR databases and analytics.
- 6 Develop standardized data architecture and governance.

Thank You

اشكرکم علی حسن استماعکم