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**EXPLORING THE MODERATING ROLE OF ARTIFICIAL
INTELLIGENCE ON THE IMPACT OF QUALITY
MANAGEMENT ON CONSTRUCTION PROJECT OUTCOMES
(A Case Study of Stormwater Program)**

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By

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قال رسول الله صلى الله عليه وسلم:

" إِنَّ اللَّهَ تَعَالَى يُحِبُّ إِذَا عَمِلَ أَحَدُكُمْ عَمَلًا أَنْ يُتَّقِنَهُ " رواه البيهقي

إهداء

إلى من كان لهما الفضل بعد الله في كل خطوة من خطوات حياتي،
والديّ الكريمين، حفظهما الله،
اللذين غرسا في نفسي حب العلم والإصرار على طلبه

إلى زوجتي العزيزة،
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إلى وطني الحبيب المملكة العربية السعودية،
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الذي أولى العلم والمعرفة عناية كبيرة،
وسعى إلى تمكين الإنسان وبناء مستقبله

إلى كل معلم أفاد، وكل باحث اجتهد،
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راجياً من الله أن يجعله نافعاً ومفيداً

الشكر والتقدير

الحمد لله أولاً وآخراً، الذي بنعمته تتم الصالحات، والذي وفقني لإتمام هذا العمل وإتمام هذه المرحلة العلمية.

ويسرني أن أتقدم بخالص الشكر وعظيم التقدير إلى الأستاذ ناصر بن إبراهيم المحيميد، الذي كان له دور بارز في نشأة هذا الكيان وتطوره، حيث حمل رؤية طموحة ومبكرة نحو تبني التعليم الإلكتروني والتعليم عن بُعد، وسعى إلى ترسيخ هذا التوجه وتطويره بما يسهم في توسيع فرص التعلم وإتاحة المعرفة للجميع. وقد كان لتلك الرؤية أثرٌ كبير في دعم هذا البرنامج وإتاحة الفرصة لإتمام هذه الدراسة.

كما أتقدم بجزيل الشكر والتقدير إلى جميع أساتذتي الكرام في برنامج الدكتوراه، لما قدموه من علمٍ وتوجيهٍ وإرشادٍ أسهم في إثراء تجربتي العلمية وتطوير معارفي البحثية.

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كما أخص أسرتي الكريمة بجزيل الشكر والامتنان على دعمهم المتواصل وصبرهم وتشجيعهم الدائم، والذي كان له الأثر الأكبر في الاستمرار والمضي قدماً حتى إتمام هذه الرسالة.

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Abstract

The construction industry continues to face persistent challenges in achieving consistent project outcomes related to cost efficiency, schedule adherence, quality performance, and stakeholder satisfaction. Despite the widespread adoption of Construction Quality Management (CQM) practices, many large infrastructure projects still experience quality deviations, rework, and performance inefficiencies. Emerging digital technologies, particularly Artificial Intelligence (AI), present new opportunities to enhance traditional quality management systems by enabling predictive analytics, automated monitoring, and data-driven decision-making. However, empirical evidence regarding how AI influences the effectiveness of CQM practices remains limited. This study therefore investigates the moderating role of artificial intelligence in the relationship between construction quality management practices and project outcomes within complex infrastructure projects.

The study adopts a mixed-methods research design combining quantitative and qualitative approaches to obtain a comprehensive understanding of the phenomenon. The quantitative component employed a structured questionnaire targeting professionals involved in infrastructure projects within the Jeddah Stormwater Program in Saudi Arabia. The survey measured four core dimensions of Construction Quality Management, quality planning, quality assurance, quality control, and quality improvement, alongside project outcome indicators including cost performance, schedule performance, quality performance, and stakeholder satisfaction. Data were analyzed using statistical techniques including reliability testing, correlation analysis, hierarchical regression, and structural equation modeling (SEM) using SPSS and SmartPLS. The qualitative component involved the analysis of project documentation, including non-conformance reports and project management records, to triangulate and contextualize the quantitative findings.

The results demonstrate a statistically significant relationship between Construction Quality Management practices and project outcomes, with CQM explaining a substantial proportion of project performance variance. The findings confirm that effective implementation of quality planning, assurance, control, and improvement contributes positively to achieving successful project outcomes. However, the statistical

analysis indicates that artificial intelligence does not yet exhibit a strong moderating effect within the tested model. Instead, AI technologies currently function primarily as operational enablers that enhance data analysis, monitoring, and decision support rather than structurally transforming quality governance systems.

The study concludes that the construction sector is presently transitioning toward an AI-enhanced quality management paradigm, where digital tools augment existing processes but have not yet fully integrated into governance frameworks. Based on these findings, the research proposes a conceptual direction for future development through the introduction of the Quality Intelligence Model (QIM), which emphasizes the early integration of AI within project quality governance to enable predictive quality management, intelligent risk detection, and data-driven project control. The study contributes to the literature on Construction Quality Management and Quality 4.0 by providing empirical evidence on the interaction between AI technologies and quality management practices within complex infrastructure environments, while offering practical recommendations for improving digital quality governance in large-scale construction projects.

المستخلص

تواجه صناعة التشييد تحديات مستمرة في تحقيق نتائج المشاريع المتعلقة بالكلفة والوقت وجودة التنفيذ ورضا أصحاب المصلحة، وذلك رغم تبني ممارسات إدارة الجودة في المشاريع الإنشائية على نطاق واسع. إذ لا تزال العديد من مشاريع البنية التحتية الكبرى تعاني من عدم تحقيق الجودة وإعادة العمل وضعف الكفاءة في الأداء. ومع التطور السريع للتقنيات الرقمية، برزت تقنيات الذكاء الاصطناعي كأحد الأدوات الواعدة التي يمكن أن تعزز أنظمة إدارة الجودة التقليدية من خلال تمكين التحليل التنبؤي ومراقبة العمليات بشكل آلي ودعم اتخاذ القرار المبني على البيانات. ومع ذلك، لا تزال الأدلة العلمية حول كيفية تأثير الذكاء الاصطناعي في تعزيز فعالية ممارسات إدارة الجودة في مشاريع التشييد محدودة. لذلك تهدف هذه الدراسة إلى استكشاف الدور المعدل للذكاء الاصطناعي في العلاقة بين ممارسات إدارة الجودة في مشاريع التشييد ونتائج المشاريع في بيئة مشاريع البنية التحتية المعقدة.

اعتمدت الدراسة منهجية البحث المختلط التي تجمع بين الأساليب الكمية والنوعية للحصول على فهم أكثر شمولية لموضوع الدراسة. في الجانب الكمي تم استخدام استبانة موجهة إلى المختصين العاملين في مشاريع البنية التحتية ضمن برنامج تصريف مياه الأمطار بمدينة جدة في المملكة العربية السعودية. وقد تضمنت الاستبانة أربعة أبعاد رئيسية لإدارة الجودة في مشاريع التشييد وهي: تخطيط الجودة، وضمان الجودة، وضبط الجودة، والتحسين المستمر للجودة، بالإضافة إلى مؤشرات نتائج المشاريع التي تشمل أداء التكلفة وأداء الجدول الزمني وجودة التنفيذ ورضا أصحاب المصلحة. وتم تحليل البيانات باستخدام عدد من الأساليب الإحصائية مثل اختبار الموثوقية ومعاملات الارتباط والانحدار الهرمي ونمذجة المعادلات الهيكلية باستخدام برنامج التحليل الإحصائي SPSS وكذلك برنامج SmartPLS. كما تم دعم النتائج الكمية بتحليل نوعي لعدد من الوثائق والبيانات المتعلقة بالمشاريع مثل تقارير عدم المطابقة والسجلات الإدارية للمشاريع مثل محاضر الاجتماعات بهدف تعزيز موثوقية النتائج وتفسيرها.

أظهرت نتائج الدراسة وجود علاقة ذات دلالة إحصائية بين ممارسات إدارة الجودة في مشاريع التشييد ونتائج المشاريع، حيث تفسر ممارسات إدارة الجودة نسبة معتبرة من التباين في أداء المشاريع. كما أكدت النتائج أن التطبيق الفعال لأبعاد إدارة الجودة الأربعة يسهم بشكل إيجابي في تحسين نتائج المشاريع. إلا أن نتائج التحليل الإحصائي أوضحت أن الذكاء الاصطناعي لا يظهر

حالياً تأثيراً تعديلياً قوياً في النموذج الإحصائي المستخدم، بل يعمل في المرحلة الحالية كعامل داعم يعزز عمليات تحليل البيانات والمراقبة واتخاذ القرار دون أحداث تحولاً جذرياً في أنظمة الجودة.

وتخلص الدراسة إلى أن قطاع التشييد يمر حالياً بمرحلة انتقالية نحو نماذج إدارة جودة مدعومة بالذكاء الاصطناعي، حيث تسهم الأدوات الرقمية في تعزيز كفاءة العمليات القائمة دون أن يتم دمجها بشكل كامل ضمن أطر الحوكمة المؤسسية للمشاريع. وبناءً على ذلك تقترح الدراسة توجهاً بحثياً مستقبلياً يتمثل في تطوير واختبار نموذج مفاهيمي لإدارة الجودة الذكية المدعومة بالذكاء الاصطناعي (Quality Intelligence Model - QIM) يركز على دمج تقنيات الذكاء الاصطناعي في مراحل مبكرة من دورة حياة المشروع بما يدعم التنبؤ بالمخاطر وتحليل بيانات الجودة واتخاذ القرارات المبنية على البيانات. وتسهم هذه الدراسة في إثراء الأدبيات العلمية في مجال إدارة الجودة في مشاريع التشييد والجودة 4.0، كما تقدم مجموعة من التوصيات العملية لتحسين حوكمة الجودة الرقمية في مشاريع البنية التحتية الكبرى.

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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
QIM	Quality Intelligence Model
QMS	Quality Management Systems
SOR	Site Observation Reports
SPC	Statistical Process Control
TQC	Total Quality Control
TQM	Total Quality Management

CHAPTER ONE

INTRODUCTION

1.1 Overview

Over the past decades, technological innovations have significantly transformed business practices across industries, with the construction sector experiencing particularly noteworthy benefits. Advancements such as Building Information Modeling, automated and robotic construction technologies, and advanced project management software have revolutionized the planning, execution, and management of construction projects (Regona et al., 2023). These tools have enhanced precision in planning, improved stakeholder communication, and optimized resource allocation, contributing to better management of project scope, cost, time, and quality. Despite these advancements, the construction industry continues to lag behind other sectors in fully leveraging emerging technologies like Artificial Intelligence (AI) to address persistent challenges in quality management (Dip Datta et al., 2024).

The construction industry continually faces difficulties in maintaining quality standards, particularly in large and complex infrastructure projects like the Jeddah Stormwater Program (JSWP). These projects involve numerous stakeholders, dynamic conditions, and high volumes of simultaneous activities, which strain traditional Construction Quality Management (CQM) practices. Issues such as material defects, utility conflicts, and inadequate compliance monitoring frequently lead to delays, cost overruns, and reduced stakeholders or customer satisfaction. Addressing these challenges requires innovative solutions, and this study explores the potential of AI enhanced CQM systems.

This research is significant for both theoretical and practical reasons. Theoretically, it investigates AI's role as a moderating variable, examining how it can optimize CQM practices and mitigate the negative impacts of project size and complexity on outcomes such as cost, time, quality, and customer satisfaction. Practically, the research focus on some AI driven technology such as machine learning, predictive analytics, natural language processing, and real-time monitoring to improve predictive capabilities, decision-making, defect detection, and automation of quality control and assurance

processes in infrastructure projects. By addressing challenges associated with AI adoption, such as costs, technical expertise, and organizational resistance, this study provides actionable insights into leveraging AI technologies in CQM.

The study is guided by three research questions: (1) the limitations of current CQM practices in large infrastructure projects, (2) the moderating role of AI in enhancing project outcomes, and (3) the barriers to adopting AI in construction projects. Through these questions, the research aims to contribute to the growing body of knowledge in construction quality management and provide a practical framework for AI adoption.

The research findings expected to offer substantial value by addressing the gaps in traditional CQM practices and demonstrating the transformative potential of AI in complex construction environments. Focusing on JSWP, the research not only highlights challenges unique to large-scale projects but also provides a replicable model for integrating AI into construction quality management globally.

1.2 Keywords

Quality Management, AI, Construction Project Outcomes, Case Study – Saudi Arabia, Stormwater, Machine Learning, Natural Language Processing.

1.3 Problem statement

The Saudi Vision 2030 outlines a bold roadmap for national transformation, with infrastructure development playing a pivotal role in improving the quality of life for citizens, fostering vibrant cities, and promoting environmental responsibility. The construction industry is instrumental in realizing these infrastructure goals that demand robust quality management in construction, highlighting the potential of AI to transform quality practices (Vision2030, n. d.). Despite its promising potential, AI adoption in Saudi Arabian construction industry remains significantly behind the global trend of technological innovation. Effective quality management is crucial for complex construction projects, yet the impact of CQM can be influenced significantly by technological factors, particularly AI (Neyestani, 2016). Research is crucial for understanding AI's moderating role and its capacity to enhance CQM by exploring how AI-powered data analysis can preemptively identify quality issues, reduce work, predict project risks, and optimize resource allocation.

1.4 Challenges in Implementing Quality Management in Construction

Implementing quality management in construction, despite its well-recognized benefits, remains a significant challenge for many organizations. Several factors contribute to the difficulties in effectively implementing robust quality management systems in the construction industry. Firstly, Zakaria et al. (2017) and Leong et al. (2014) indicated that a major challenge in the construction industry is its project-based nature, where each project is unique and often involves numerous stakeholders, subcontractors, and varying site conditions. In contrast, industries such as manufacturing focus on the mass production of standardized products, allowing for greater control over processes and environments (Rezaei, 2011). This fundamental difference significantly influences how construction projects define, measure, and manage quality.

Secondly, the fragmented and decentralized nature of the construction industry makes it challenging to implement organization-wide quality management systems. The high degree of customization in construction projects, the dynamic nature of construction activities, and site-specific conditions inherent in construction projects make it difficult to standardize processes and achieve organization-wide quality control (Tang et al., 2005). Furthermore, construction projects often face constraints such as tight budgets, short timelines, and changing client requirements, which can compromise the ability to prioritize and invest in robust quality management practices.

Thirdly, the construction industry's resistance to change and a lack of awareness and commitment to quality management principles among some construction professionals can impede the successful adoption of quality management systems. These inherent complexities, along with deep-rooted cultural barriers within the industry, pose significant hurdles in realizing the full potential of quality management practices in construction projects. The reluctance to embrace new approaches and the entrenched mindsets of some construction stakeholders can create obstacles to implementing effective quality management initiatives, hindering the optimization of construction project outcomes (Abioye et al., 2021).

In addition to these factors, the author's experience with the JSWP has highlighted the inherent complexity and variability of construction projects, further complicating the implementation of robust quality management systems. JSWP, with its numerous

ongoing and unique projects spread across all sides of Jeddah, demonstrates how the involvement of multiple stakeholders, subcontractors, and ever-changing site conditions can challenge standardization and consistent quality control. These challenges are further compounded by varying levels of client involvement and the geographically dispersed nature of the projects and inadequate staffing levels, which strain supervision capacity and make it even more difficult to ensure adherence to quality standards.

Despite JSWP projects being similar in concept and executed by the same contractors, they continue to encounter persistent issues. These issues include material defects, supply and handling challenges, and inadequate quality control measures, which compromise the effectiveness and efficiency of the construction efforts. The projects need adequate supervision, which is exacerbated by the increased high volume of simultaneous projects, leading to frequent utility conflicts and substantial delays. These conflicts often result in prolonged processes for coordination with other stakeholders, modification and approvals of shop drawings and execution methods. Such delays increase resident complaints due to prolonged excavation works, extended closures of roads, escalating the cost of reworks, and extending the overall project's progress.

Moreover, constraints such as tight budgets, short timelines, customer satisfaction, and shifting client demand place pressure on prioritizing quality over immediate deliverables. Combined with that resistance to change and varying levels of awareness and commitment among construction professionals further impede the adoption of effective CQM. Addressing these challenges within JSWP, and more broadly in construction, requires a dedicated effort to foster a quality culture, enhance awareness, and leverage innovative solutions, such as AI-driven CQM practices, to streamline processes and deliver better project outcomes.

Recent study by Zakaria et al. (2017) identifies several challenges in flood mitigation projects that hinder successful implementation of CQM. These include inadequate planning, poor stakeholder coordination, ineffective resource allocation, and inconsistent adherence to project standards and master plans. Such challenges disrupt project workflows, lead to delays, and compromise overall project quality. Another study by Hwang and Yang (2014) highlights rework as a major contributor to project

delays, with its root causes often tied to quality-related issues such as design errors, inadequate quality control, and poor adherence to project specifications. The research underscores the importance of proactive quality management in minimizing rework, noting that early identification and resolution of potential quality issues can significantly reduce disruptions and improve project schedules and cost.

Similar challenges are evident in JSWP, where gaps in planning, stakeholder alignment, and non-compliance with quality management processes, such as Method of Statements (MOS) and Inspection Testing Plans (ITP), exacerbate inefficiencies across its large-scale projects. The Taunsa Barrage Rehabilitation and Modernization Project in Pakistan study by Khan et. al (2006) highlights similar issues, such as inadequate adherence to quality practices due to increased workload and complexity of work, underutilization of statistical sampling methods, and limited stakeholder awareness and commitment to quality practices, which significantly hinder Quality Assurance (QA) and Quality Control (QC) efforts.

These shared challenges underscore the need for robust, project-specific quality management practices to address recurring inefficiencies and ensure better outcomes. For JSWP, integrating AI-driven technologies could serve as a transformative solution, enabling automated compliance monitoring, optimizing resource allocation, and providing real-time insights. By addressing these foundational gaps and leveraging advanced technologies, JSWP can enhance coordination, reduce rework, and improve overall project performance across its dispersed and complex infrastructure initiatives.

However, more research will be needed to understand how integrating AI with quality management practices impacts construction project outcomes, particularly within the Saudi Arabian context (Datta et al., 2024). Existing global studies often emphasize the general advantages of AI in construction, such as its impact on project outcomes or its application to specific quality management issues. However, they rarely address the unique challenges and established practices specific to the Saudi Arabian construction sector nor overall effect on quality management system. Therefore, more focused research is needed to investigate and understand the effect of AI on the overall CQM, to ensure our understanding of effectively integrating these technologies with existing quality practices to optimize project outcomes.

1.5 Purpose of the Study

Given the potential benefits of AI in improving construction project outcomes through enhanced quality management, this research aims to explore the moderating role of artificial intelligence in improving the effectiveness of CQM practices in construction projects. The study focusses on infrastructure projects, which are typically complex and involve multiple stakeholders. They are crucial in driving economic growth, improving quality of life, and fostering long-term sustainability in the Saudi Arabian construction industry. The specific objectives of the study are:

1. **Comprehensive Review:** Conduct a comprehensive review of empirical studies that investigate the impact of AI on construction CQM practices and project outcomes, aiming to synthesize key findings and identify gaps in the current literature.
2. **Evaluate CQM Practices:** Assess the limitations of traditional CQM practices in addressing the challenges posed by the size and complexity of infrastructure projects, particularly within JSWP.
3. **Examine AI's Impact:** Investigate the potential of AI technologies to enhance CQM practices focusing on AI's moderating role in mitigating CQM practices insufficiencies, with a focus on improving project outcomes such as cost efficiency, schedule adherence, quality, and customer satisfaction.
4. **Identify AI challenges:** Based on insights gathered from the selected contractors and projects data, identify and analyze the challenges associated with implementing AI-driven CQM practices in infrastructure projects.
5. **Develop Strategies and Frameworks:** Propose practical strategies and frameworks for effectively integrating AI-driven CQM practices, ensuring improved outcomes in large and complex infrastructure projects.
6. **Explore future opportunities:** Explore emerging opportunities for AI to enhance CQM practices in infrastructure projects further and outline future research directions based on the findings from the study.

1.6 Significance of Study

1.6.1 Theoretical Contributions

This research seeks to fill a significant gap in construction management literature by empirically investigating the moderating role of AI in quality management within construction projects. It will enhance theoretical frameworks by integrating advanced AI technologies, such as Machine Learning (ML) and Natural Language Processing (NLP) and examining their impact on the effectiveness of quality management practices. This study also contributes to a deeper academic understanding of how AI can be systematically applied to improve construction project outcomes, through enhanced CQM practices offering a new perspective on the interplay between technology and project management.

1.6.2 Practical Implications

The study is poised to offer substantial value to the construction industry, particularly within the context of JSWP. The findings help to develop more efficient, cost-effective, and high-quality construction practices by exploring and validating AI-driven quality management approaches. The insights gained could lead to the development of refined AI-enhanced quality management frameworks that reduce rework, delays, cost of poor quality, and improve stakeholder satisfaction, thus providing a model for future construction projects in Saudi Arabia.

1.6.3 Expected Added Value

The integration of AI in managing complex infrastructure projects, as explored in this study, aligns with the strategic goals of Saudi Vision 2030. The successful application of AI in the JSWP could serve as a benchmark for the national construction industry, promoting broader adoption of intelligent technologies. This research provides actionable strategies for leveraging AI to overcome common quality management challenges, enhancing project delivery across the board. Furthermore, the study recommends that policymakers, project managers, and industry professionals adopt AI-driven solutions, potentially transforming construction practices nationally and internationally.

1.7 Research Methodology

This study employs a mixed-methods research approach, combining in-depth qualitative case study and comprehensive quantitative data analysis, to thoroughly investigate the relationship between CQM practices, construction project outcomes, and the moderating influence of Artificial Intelligence technologies. The qualitative component provides rich contextual insights, exploring how AI-enabled CQM processes are implemented and integrated within real-world construction projects. The quantitative analysis then examines the statistical significance and magnitude of the moderating effect of AI on the link between CQM and key project outcomes, such as reduced rework, enhanced productivity, improved cost and schedule performance. This holistic mixed-methods approach yields a deeper understanding of the complex interplay between quality management, AI, and construction project success.

1.7.1 Data Collection, Sampling and Analysis

Primary data was collected through structured surveys from stakeholders involved in JSWP and similar infrastructure projects. The targeted participants included project managers, quality professionals, construction teams, engineers, contractors, suppliers, and other professionals with direct involvement in construction quality management or AI-related practices. Secondary data were gathered from project documentation, industry reports, academic journals, case studies, and other relevant literature on the application of Artificial Intelligence technologies in the context of construction quality management. This comprehensive secondary data collection provides a robust understanding of the current state of research and industry practices in leveraging AI to enhance not only project management, but also quality management processes and outcomes in construction projects.

A purposive, non-proportional stratified sampling strategy was used in this study to ensure that participants had direct experience with Construction Quality Management, infrastructure projects, and AI-related practices. The non-proportional stratified element ensured representation from key stakeholder groups, including participants from JSWP stakeholders (Client, Consultants, Contractors, Sub-Contractors, and Suppliers), and other similar infrastructure projects.

To ensure comprehensive insights, the sample included a diverse set from various roles within the program, project managers can provide perspectives on overall project execution and quality management integration, while quality control and assurance teams can highlight the application and challenges of current CQM practices. Engineers and site supervisors offer practical insights into quality-related issues, site related delays, and AI possible implementation on-site.

Additionally, involving other key disciplines such as planning engineers allows for exploring how AI can optimize scheduling, anticipate quality related delays, and enhance time management. Cost control engineers also can contribute insights into cost forecasting and budget management, focusing on how AI aids in controlling project expenses. Technical engineers provide knowledge about design and specifications, and utility issues, emphasizing AI's role in streamlining technical solutions and design reviews. Clients or regulatory representatives ensure a focus on compliance and stakeholder satisfaction, while AI or technology specialists can offer expertise on the deployment and potential of AI technologies. This multidisciplinary approach ensures a holistic understanding of the integration of AI into CQM practices in large infrastructure projects. Quantitative data from surveys will be analyzed using statistical Tools such as SPSS.

1.8 Theoretical background

The concept of quality management has evolved significantly since its early applications in manufacturing, transforming industries by promoting consistency, efficiency, and customer satisfaction. Initially focused on basic inspection and defect detection, quality management has developed into a sophisticated system that integrates planning, control, and continuous improvement to enhance organizational performance. This evolution reflects an increasing awareness that quality is not merely a production issue but a fundamental organizational objective (Daneshjo et al., 2021). In construction, where project complexity and stakeholder expectations are high, robust quality management is crucial for meeting performance goals and sustaining competitive advantage.

Several pioneering figures, often called quality management "gurus," laid the groundwork for modern quality practices. Walter Shewhart, often called the father of statistical quality control, introduced the concept of control charts to monitor process variability in the 1920s. Building on Shewhart's ideas, W. Edwards Deming promoted continuous improvement through his PDCA cycle (Plan-Do-Check-Act) and emphasized data-driven decision-making. In the 1950s, Joseph Juran introduced the Quality Trilogy, quality planning, control, and improvement, which underscored the importance of quality as a company-wide responsibility (ASQ, 2024).

Philip Crosby added to this foundation with his philosophy of zero defects and the idea that "quality is free," advocating for preventive measures over costly corrections. Armand Feigenbaum introduced Total Quality Control (TQC), asserting that quality should be integrated across all departments (Huggins, 1998). At the same time, Kaoru Ishikawa emphasized the role of collaborative problem-solving and developed tools like the fishbone diagram for root-cause analysis. Building on these traditional quality foundations, Quality 4.0 has recently emerged as a contemporary extension that integrates digital technologies, data-driven systems, automation, and artificial intelligence to enhance quality planning, assurance, control and continuous improvement (Zonnenshain & Kenett, 2020).

These contributions have influenced modern project management, where achieving project success depends on balancing the Triple Constraint; scope, cost and time. In construction, changes to any of these factors, such as an accelerated timeline, can impact both the budget and the quality of the outcome, posing significant challenges for project managers. Customer satisfaction further reinforces these constraints to measure project success, reflecting whether the project meets or exceeds client expectations. The principles established by the quality pioneers provide a theoretical foundation for understanding how quality management practices can help optimize this balance, especially when complemented by modern tools such as AI driven technology. In this context, Quality 4.0 offers a valuable contribution by extending traditional quality principles through digital technologies, data-driven decision making, automation, risk prediction, automation, and intelligent monitoring to support more responsive and predictive quality management in complex construction projects.

1.9 Construction Quality Management (Independent Variable)

This study examines Construction Quality Management (CQM) as independent variable influencing project outcomes, with Artificial Intelligence (AI) as a moderating factor. In construction projects, CQM refers to the structured application of quality planning, assurance & control, and improvement practices to ensure that project deliverables comply with contractual requirements, technical specifications, regulatory standards, and client expectations. Effective CQM practices are essential for reducing defects, minimizing reworks, controlling quality-related costs, improving efficiency, and supporting successful project delivery (lue et al., 2022).

The PMBOK defines Quality Management as the process of determining quality policies, objectives, and responsibilities so that the project will satisfy the needs for which it was undertaken (PMI, 2021). In the construction context, this requires ensuring that project deliverables meet specifications, regulatory requirements, client expectations and performance objectives.

The concept of quality has been shaped by several important theoretical perspectives. Crosby's definition of quality as "conformance to requirements" emphasizes the importance of meeting predefined standards and preventing defects from the beginning of the project, which is closely related to quality planning and early prevention (ASQ, 2024). Juran and Godfrey concept of "fitness for use" expands this view by emphasizing that constructed facilities should not only comply with specifications but also perform their intended functions effectively throughout their lifecycle (Juran & Godfrey, 1999). Similarly, quality in construction is also associated with fulfilling stakeholders' expectations, including those of clients, contractors, consultants, subcontractors, designers, and end users (Khan et. al., 2008).

Within this study, CQM is viewed as an integrated management approach that coordinates quality-related activities throughout the project lifecycle. Sogaxa et al. (2021) defines CQM as a management approach that ensures construction processes are completed according to specified quality requirements, within time, budget, and safety expectations. Neyestani (2016) similarly describes CQM as the coordination and integration of quality assurance and quality control activities throughout the project life

cycle to achieve project objectives. These definitions support the view that effective CQM requires the alignment of planning, assurance & control, and improvement activities to achieve project outcomes related to cost, schedule, quality, and customer satisfaction.

For the purposes of this research, CQM is operationalized through four dimensions: Quality Planning, Quality Assurance, Quality Control, and Quality Improvement. This structure builds on established quality management principles while reflecting the practical division of quality responsibilities in construction projects. Quality planning focuses on defining quality objectives, procedures, responsibilities, and performance indicators. Quality assurance addresses system-level governance, audits, compliance checks, and process effectiveness. Quality control focuses on work inspections and testing, defect identification, and non-conformity and observation reporting. Quality improvement addresses corrective and preventive actions, and measurable quality management practices.

The author from practical experience in large infrastructure and mega projects, CQM can be defined as a systematic process supported by strategic goals established earlier during the project planning stage toward fulfilling project quality objectives through a preventive approach. This approach can be enhanced by using AI as a predictive tool to improve efficiency, prevent defects, and reduce the cost of reworks in construction projects by preventing defects before occurrence.

1.9.1 Quality Planning

The PMBOK (PMI, 2021) defines Quality Planning as "the process of identifying quality requirements and/or standards for the project and its deliverables and documenting how the project will demonstrate compliance." It aligns with Juran's definition of establishing the goals and process required to meet quality standards from the outset (Juran & Godfrey, 1999). In the construction industry, this means defining the necessary quality standards for materials, processes, and final outputs, setting clear expectations for quality from the outset, and establishing procedures for meeting these standards. Effective quality planning is crucial for establishing quality benchmarks, defining roles and responsibilities, and documenting the quality management strategy.

The use of historical data from previous projects, including lessons learned, NCRs / SORs, defect records, inspection results, and recurring quality issues, can further strengthen quality planning by helping project teams anticipate risks, identify common sources of non-compliance, and develop more effective prevention strategies before execution begins. A well-crafted quality plan should therefore outline the actions required at each project phase to achieve the targeted quality standards and use available historical evidence to support proactive decision making (Neyestani, 2016).

1.9.2 Quality Assurance (QA)

In Construction Quality Management, Quality Assurance (QA) and Quality Control (QC) play complementary roles in maintaining and improving project quality. According to the PMBOK (PMI, 2021), QA is "the process of auditing the quality requirements and the results from quality control measurements to ensure appropriate quality standards and operational definitions are used." QA in construction is proactive, aiming to prevent defects through regular inspections, testing, and monitoring, ensuring that work meets the established quality plan and specifications. Juran's Quality Control Handbook (Juran & Godfrey, 1999) expands on this by defining QA as a process that instills confidence that quality requirements will be met throughout the project. Juran emphasizes the importance of developing robust systems and preventive measures and conducting audits to verify compliance with quality standards and ensure consistency and reliability across project phases.

1.9.3 Quality Control (QC)

On the other hand, QC is more hands-on and focuses on detecting and correcting quality issues. Defined by Juran and Godfrey (1999) as "the process of evaluating quality performance, comparing that performance with standards or goals, and acting on the difference," QC emphasizes feedback loops and corrective actions, making it a cyclical process aimed at continuous improvement. QC includes practical and operational techniques for measuring and controlling the characteristics of materials, structures, and systems to meet quality requirements. It operates as a "detection mode," identifying existing issues and facilitating corrective actions. QC systems provide displays of non-conformance to highlight areas requiring attention, allowing for data-driven problem identification and management (Tang. et al., 2005).

In the construction industry, QA and QC form a comprehensive quality framework in construction quality management. QC procedures often include daily inspections, quality reporting, and minimizing output variation, ensuring standards consistently met across all project stages. QA establishes preventive processes and systems, while QC detects and addresses deviations from quality standards. This dual approach is essential in construction, where complex projects demand proactive quality assurance and rigorous control over the work that will be executed.

1.9.4 Quality Improvement

The third component of Juran's Quality Trilogy, Quality Improvement, is defined by PMBOK (PMI, 2021) as "the process of enhancing the organization's processes to improve the project's outcomes" This dimension continuously refines processes, systems, and practices to improve construction quality, reliability, and consistency. Quality Improvement involves analyzing performance, identifying opportunities for enhancement, and implementing changes to address the root causes of issues. Common practices include post-project reviews, benchmarking against industry standards (Crosby, n.d), and incorporating Lean Construction and Six Sigma methodologies to streamline processes and minimize inefficiencies. By embracing a culture of continuous improvement, construction organizations can systematically enhance the quality of their project deliverables and outcomes over time.

1.10 Construction Projects outcomes (dependent Variable)

Construction project outcomes are multidimensional, encompassing factors such as safety, quality, schedule, cost, and customer satisfaction. Effective quality management is crucial to achieving positive project outcomes across these critical dimensions. PMBOK defines project outcomes as the outputs and benefits that result from project activities, which should align with the organization's strategic objectives and provide value to stakeholders. While ISO 21500 defines project outcomes as meeting the predefined criteria for success, including cost, time, quality, and stakeholder satisfaction. This study measures project outcomes by four key indicators: Cost, Time (or Schedule), Quality, and Customer Satisfaction. These indicators are chosen in this research as they are universally recognized and used as the core dimensions of project performance in construction management.

Cost represents the financial efficiency of the project, aiming to minimize expenses while maintaining standards. Time measures adherence to timelines, as delays can lead to cost overruns and client dissatisfaction. Quality ensures the project meets all specifications and is durable, safe, and fit for purpose. Also, Poor quality can lead to rework, increased costs, safety hazards, failure to meet regulatory requirements, and reduced customer satisfaction (Hwang & Yang, 2014). Prioritizing quality ensures that the final product fulfills its intended purpose and provides long-term value to the client and end-users. Finally, customer satisfaction reflects the degree to which the project meets or exceeds client expectations, which is crucial in assessing the project's overall success. These four indicators are interdependent and collectively capture the balance of efficiency, effectiveness, and stakeholder value that defines a successful construction project (Neyestani, 2016) (Kiew et al., n.d.).

Project outcomes are particularly crucial in construction, as they determine the project's viability, efficiency, and overall quality, directly impacting client and end-user satisfaction. Effective project outcomes are essential in the construction industry, where complex, large-scale projects require adherence to high standards and regulatory compliance (Low & Ong, 2014). Also, involving multiple stakeholders, regulatory requirements, and high-risk activities, require managing cost, time, quality, and customer satisfaction to navigate these complexities, by integrating AI technology into QMS, the study aims to enhance these outcomes, demonstrating practical relevance.

1.11 Artificial Intelligence (Moderating Variable)

Several sources defined Artificial Intelligence (AI) and its related technologies, emphasizing its role in developing intelligent machines that can perform tasks traditionally requiring human intelligence (Chouchene et al., 2020). AI is a branch of computer science dedicated to creating machines capable of visual perception, speech recognition, decision-making, and language translation. Some definitions focus on AI's ability to mimic or replicate human cognitive functions, such as thinking, creativity, and planning (Nagireddy, 2023). Additionally, AI combines computer science and large datasets to solve complex problems, automating tasks typically reliant on human intelligence. In broader terms, AI is the science of developing intelligent systems and models that can replicate human cognitive processes, thus creating systems that enhance and streamline various tasks across multiple industries (Abioye et al., 2021).

AI technology includes tools like ML, CV, NLP, and predictive analytics, which significantly benefit many fields, including construction. ML helps identify patterns in large datasets, enabling predictive insights, while CV automates inspections and defect detection, improving accuracy. These technologies streamline tasks, reduce errors, and enhance decision-making, offering efficient, data-driven support to complex projects (Sahadevan, 2023).

Several AI platforms offer robust tools suited explicitly for data analysis that can support quality management in construction by predictive modeling and process automation. **Google AutoML** enables users to create custom ML models that detect patterns and predict outcomes without extensive coding expertise (Google Cloud, 2024). **Microsoft Azure AI** provides a suite of AI services, including CV and NLP, that can automate inspections, detect defects, and facilitate project monitoring in real-time (Microsoft, 2024). **IBM Watson** offers advanced predictive analytics and ML capabilities to process complex construction data to forecast potential risks and support data-driven decision-making (IBM, 2024). Beyond these established enterprise platforms, emerging AI systems such as Anthropic's Claude, Agentic AI, and Manus increasingly integrate ML and NLP capabilities within unified analytical environments. It helps users and organizations to enable analysis of large volume of project documents and operational data to generate actionable insights and fast track repetitive works.

In construction, AI technology transforms quality management practices by providing real-time insights, automating quality inspections, and predicting potential issues before they arise. For instance, computer vision algorithms can detect defects during construction activities, reducing reliance on manual inspections and improving accuracy. Predictive analytics, powered by AI platforms, can also analyze project data to identify trends, recurring issues, and provide early warning indicators allowing project teams to implement corrective and preventive actions proactively. The value of these AI capabilities can be further increased when integrated with established project management and document control platforms such as Aconex and Unifier, as these platforms already contain structured project data, workflows, approvals, NCRs, submittals, correspondence, and quality related records. Integrating AI with such platforms can shorten the adoption gap by using existing digital workflows instead of requiring organizations to build entirely new systems.

These capabilities align with the quality management principles of Deming, Juran, and Feigenbaum as well as Quality 4.0 by strengthening data-driven decision-making, strategic planning, process control, and organizational wide quality responsibility. Therefore, in this study, AI is examined as a potential moderating factor and operational enhancer that may support more efficient, consistent, and reliable quality outcomes in response to the evolving demands of the construction industry (Seyman-Güray, 2023).

In conclusion, integrating quality management theories with AI technology provides a comprehensive framework for understanding and improving construction project outcomes. By grounding this research in the philosophies of quality management pioneers, this study aims to demonstrate how AI can systematically enhance the effectiveness of quality management practices, ultimately leading to better outcomes in cost, time, quality, and customer satisfaction within the construction industry.

1.12 Practical Background

The Jeddah Storm Water Program, tasked with a significant overhaul of the city's stormwater management systems, involves 92 projects that incorporate similar construction activities such as excavation, laying network pipes, installation of manholes and catch basins, and construction of marine outfalls and pumping stations. The JSWP was chosen as a case study as these projects face significant challenges in maintaining quality standards due to the complexity of the work, tight timelines, and the dynamic nature of the construction environment as well as utility clashes. This setting offers a unique opportunity to investigate how CQM practices perform under demanding conditions and to evaluate AI's potential to address these challenges effectively (JSWP, 2021).

Despite the projects being similar in concept and executed by the same contractors, these projects consistently face recurring challenges that hinder their progress. Issues such as material defects, supply and handling difficulties of materials, lack of site supervision, and inadequate quality control measures compromise construction efficiency and effectiveness. Additionally, the high volume of simultaneous projects strains supervision capacity, leading to frequent utility conflicts and significant delays. These conflicts often result in prolonged design changes and approvals, frequent shop

drawing modifications, extended excavation activities, escalating rework costs and increasing resident complaints. Together, these factors disrupt the JSWP program timelines and negatively impact overall project outcomes.

Moreover, a critical challenge exacerbating these problems is some contractors' non-compliance with established work procedures and method statements. This disregard for producers leads to quality issues and undermines strategic quality management efforts to meet project standards. Integrating advanced monitoring and compliance technologies, such as AI, is imperative. Projects can promptly identify deviations and enforce corrective actions by leveraging AI to automate compliance checks and monitor adherence to method statements in real-time. This proactive approach mitigates the risk of non-compliance and enhances overall project delivery.

Compounding these challenges, the risk associated with the rainfall season can have severe impacts on both ongoing construction projects and surrounding residential areas if not managed promptly and effectively. The dynamic nature of construction, coupled with tight timelines, heightens the risk of disruptions. Effective quality management, supported by AI-driven predictive analytics and automation, can mitigate these risks, ensuring projects are delivered efficiently, on budget, and to high standards.

Integrating AI technologies into JSWP offers transformative solutions to overcome the recurring challenges faced by the projects. AI-driven tools, such as predictive analytics, can enhance material quality control by identifying defects and optimizing supply chain management. Automated compliance systems ensure strict adherence to method statements and established protocols, reducing the risk of quality lapses caused by contractor non-compliance. Furthermore, AI's ability to forecast potential utility clashes, and simulate design scenarios enables proactive planning, minimizing delays and costly rework. During critical periods like the rainfall season, AI's predictive capabilities can help anticipate risks, prioritize interventions, and safeguard ongoing projects and surrounding residential areas. By leveraging AI, JSWP can significantly enhance efficiency, consistency, effectiveness of CQM practices, ensuring improved project outcomes despite the complexities and dynamic conditions of the program.

This research aims to fill the gap by focusing on integrating AI into CQM practices, particularly in stormwater network projects, examining several vital aspects, and identifying the most impactful ways to tailor AI solutions to the unique context of Saudi Arabia's construction industry. Successful Integration of AI will benefit JSWP in overcoming some of the quality issues and concerns in the following four significant areas of quality management:

1. **Quality Planning:** Exploring how AI-enhanced planning can be used to improve overall quality and mitigate cost overruns and delays, improving economic and temporal efficiency in stormwater network projects.
2. **Quality Control:** Analyzing how AI-driven tools can be used to detect/predict and correct defects early in construction.
3. **Quality Assurance:** Assessing AI's role in enhancing adherence to quality standards and project requirements, which are crucial for the integrity of stormwater projects.
4. **Quality Improvement:** Investigating how AI can contribute to the sustainability and resilience of stormwater networks, through failure detection, and recommending preventive measures based on pattern recognition from historical data.

1.12.1 Research Questions

Against this backdrop of exploring AI's potential to transform areas of CQM practices, the research is structured around three critical questions:

Research Question 1: How do project size, complexity, multiple stakeholders, and high volumes of concurrent activities affect the sufficiency of traditional CQM practices in large scale infrastructure programs such as Jeddah Stormwater Program?

- Question 1.1: Do the challenges of managing large and complex infrastructure projects lead to schedule delays, as CQM practices become inadequate in mitigating challenges?
- Question 1.2: Do the size and complexity of infrastructure projects contribute to cost overruns, as CQM practices become insufficient in preventing these overruns?
- Question 1.3: Do the size and complexity of infrastructure projects negatively affect customer satisfaction, and CQM practices are unable to address these concerns effectively?

- Question 1.4: Do the size and complexity of infrastructure projects result in substandard quality outcomes, as CQM practices fail to maintain consistent quality under such conditions?

Research Question 2: Do AI-driven CQM practices in JSWP modify the impact relationship between quality management and project management outcomes?

- Question 2.1: Do the AI-driven practices of Quality Planning in JSWP modify the impact relationship between CQM and project management outcomes?
- Question 2.2: Do the AI-driven practices of Quality Control in JSWP modify the impact relationship between CQM and project management outcomes?
- Question 2.3: Do AI-driven practices of Quality Assurance in JSWP modify the impact relationship between CQM and project management outcomes?
- Question 2.4: Do the AI-driven practices of Quality Improvement in JSWP modify the impact relationship between CQM and project management outcomes?

Research Question 3: What are the financial, organizational, ethical and technical challenges associated with adopting AI technologies in construction projects, and how do these barriers impact the effective integration of AI into CQM practices?

- Question 3.1: Does the cost of implementing AI technologies create significant barriers to their adoption in CQM practices?
- Question 3.2: Does resistance to change among stakeholders and organizational culture negatively impact the adoption of AI technologies in construction projects?
- Question 3.3: Does the lack of high-quality data, integration challenges, or insufficient technical expertise hinder the effective implementation of AI in CQM?
- Question 3.4: Does the skills gap in the construction industry limit the adoption and successful utilization of AI technologies?
- Question 3.5: Do concerns of data privacy, algorithm bias, regulatory compliance affect the willingness of construction organizations to adopt AI technologies?

1.12.2 Hypothesis

CQM is essential for ensuring projects' success and sustainability in the rapidly evolving construction industry. The first hypothesis is intended to establish the contextual problem of the study, namely that the size and complexity of large infrastructure programs can place a pressure on traditional CQM practices and reduce

their sufficiency in addressing recurring quality challenges, as well as the ability to predict and prevent it. With the ongoing development of AI, there is significant interest in leveraging its capabilities to enhance the efficiency, accuracy, predictability and overall ability of CQM practices. Through this approach, the study aims to offer a comprehensive analysis of AI's role in refining CQM processes and its broader implications on the efficiency and success of infrastructure projects. The following hypotheses were formulated to guide this investigation:

Hypothesis (H1): In large and complex infrastructure programs, traditional CQM practices become insufficient to fully address recurring quality-related challenges, which negatively affects project outcomes.

- Hypothesis (H1a): Project size and complexity strain traditional CQM practices and contribute to recurring issues such as defects, non-conformities, rework, and repeated site observations.
- Hypothesis (H1b): The insufficiency of traditional CQM practices in complex infrastructure programs contributes to schedule-related challenges, including delays in approval, corrective actions, inspections, and project progress.
- Hypothesis (H1c): The insufficiency of traditional CQM practices in complex infrastructure programs contributes to cost-related impacts, including rework, inefficient resource use, and cost of poor quality.
- Hypothesis (H1d): The insufficiency of traditional CQM practices in complex infrastructure programs negatively affects stakeholders and customer satisfaction.

Hypothesis (H2): AI-driven CQM practices significantly modify the relationship between CQM practices and project management outcomes, enhancing cost efficiency, schedule adherence, quality of deliverables, and customer satisfaction.

- Hypothesis (H2a): AI-driven CQM practices significantly enhance the quality of deliverables in infrastructure projects by improving defect detection, prevention and reducing rework.
- Hypothesis (H2b): AI-driven CQM practices significantly reduce cost overruns in infrastructure projects by reducing the cost of rework and cost of poor quality.
- Hypothesis (H2C): AI-driven CQM practices significantly reduce schedule delays in infrastructure projects by minimizing rework through proactive defect detection and quality monitoring.

- Hypothesis (H2D): AI-driven CQM practices significantly enhance customer satisfaction in infrastructure projects by improving responsiveness to quality issues, reducing recurring defects and rework, and supporting faster corrective actions,

Hypothesis (H3): Financial, organizational, ethical, and technical challenges significantly limit the effective integration of AI technologies into CQM practices withing construction and infrastructure projects.

- Hypothesis (H3a): Financial constraints, such as implementation and operational costs, significantly limit the adoption of AI technologies in CQM practices.
- Hypothesis (H3b): Organizational barriers, including resistance to change & lack of skilled personnel, significantly impact the integration of AI into CQM practices.
- Hypothesis (H3c): Ethical concerns, such as data privacy, algorithmic bias, and job displacement fears, significantly hinder the adoption of AI in CQM practices.
- Hypothesis (H3d): Technical challenges, including insufficient data quality and integration difficulties, significantly reduce the effectiveness of AI technologies in improving CQM practices.

Figure (01) illustrates the conceptual framework for this study, highlighting the relationships between the independent variable (Construction Quality Management Practices), the dependent variable (Project Management Outcomes), and the moderating role of (AI Technologies).

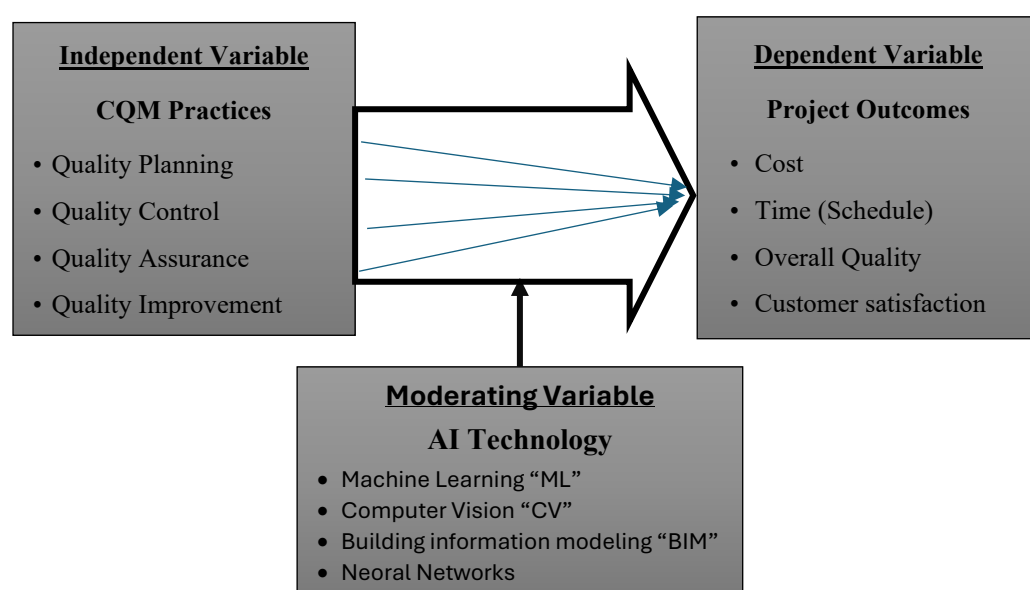


Figure 01 - The diagram represents the variables and their relationships
Source: prepared by the researcher

1.13 Literature Review

1.13.1 Quality Management Systems in Construction

Quality management systems are crucial for improving the performance of organizations, especially in the construction industry. Research has shown that QMSs can significantly impact customer satisfaction, cost control, time management, and overall quality (Leong et al., 2014) (Aichouni et al., 2014). Neyestani (2016) emphasizes the impact of QMS on these four crucial aspects of construction projects. Furthermore, a study in the Saudi construction industry supports Oakland & Marosszeky's (2006) statement that the industry needs to embrace total quality management concepts and QMS, especially during growth and rapid expansion.

The effectiveness of a quality management system in construction projects can provide better control over project processes and workflows. Studies conducted across diverse construction markets, including Saudi Arabia, UAE, India, China, Pakistan, USA, and South Africa, have all demonstrated the benefits of implementing robust quality management systems to enhance project outcomes, improve cost control, enhance time management, and increase overall customer satisfaction and industry performance (Likita et al., 2018).

1.13.2 Challenges in Implementing CQM

The study conducted by Hamdan (2024) on a stormwater network project in the UAE highlighted that the strict implementation of CQM practices is critical for meeting required standards and customer needs. Such an adherence not only increases the project's lifecycle but also reduces maintenance costs and improves sustainability. The author explained on the case study the importance of implementing quality processes and procedures at every stage of the project, including material testing, site activities, and project documentation, such as shop drawings, MOS and ITP. In the context of JSWP, shop drawings, MOS and ITP have proven to be a significant challenge, as contractors often fail to adhere to these requirements as outlined in the quality plan. This non-compliance undermines the effectiveness of CQM practices, leading to recurring issues such as substandard workmanship, defects, and rework.

Another study by Othman et. al. (2018) highlights other challenges in implementing Quality Management Systems (QMS) in Malaysian construction projects for high rise construction, including limited knowledge of QA/QC procedures, inadequate supervision, and poor worker attitudes. These challenges are compounded by high material waste and excessive workloads for QA/QC personnel, leading to inefficiencies in achieving quality standards. The study proposes a structured framework to address these issues, emphasizing management commitment, enhanced documentation, and resource optimization.

A study conducted in Jordan by Khatatbeh, A. (2014) underscores significant challenges that impede effective QM practices, including a lack of senior management commitment, insufficient planning for quality management, poor coordination between stakeholders, and unclear allocation of quality responsibilities. Additionally, the findings reveal that inadequate staff training and resistance to adopting structured quality frameworks hinder the consistent application of QM processes. These challenges collectively impact the ability of construction projects to meet desired quality standards, emphasizing the need for stronger organizational alignment and proactive quality planning to overcome these obstacles.

The case study by Abdullah et al. (2008) examines the implementation of QMS in the Kuala Lumpur International Airport (KLIA) project, emphasizing the challenges associated with managing quality in large-scale and complex projects. The study highlights issues such as integrating multiple Project Quality Plans (PQP), coordinating diverse stakeholders, and ensuring compliance with statutory requirements and project-specific standards. These challenges were addressed through structured processes for inspections, testing, and audits.

Similarly, The Jeddah Stormwater Program exemplifies the critical importance of CQM in addressing the common challenges faced worldwide in large-scale, complex construction projects. As a multifaceted endeavor, JSWP demands meticulous planning, rigorous quality control, and a commitment to continuous improvement to mitigate the impact of size and complexity on project outcomes. Insights from case studies highlight the difficulties of integrating multiple PQP, coordinating diverse stakeholders, and ensuring compliance with statutory and project-specific standards

challenges mirrored in the JSWP. The UAE stormwater network case emphasizes the importance of strict adherence to quality management processes, including MOS and ITP, to prevent non-compliance, defects, and rework.

By leveraging the principles of Juran's Quality Trilogy, including quality planning, assurance, and improvement, and incorporating AI-driven solutions, the JSWP can address these challenges proactively. AI technologies, such as automated compliance monitoring and predictive analytics, can enhance planning accuracy, streamline quality control measures, and identify improvement opportunities across the program's dispersed projects. Together, these approaches can enable the delivery of a high-quality, efficient, and timely stormwater management system for the city of Jeddah, ensuring alignment with both project goals and stakeholder expectations.

1.13.3 Quality Planning

Quality planning is crucial to effective QMS in construction projects. It involves clearly defining the project requirements, identifying the critical quality characteristics that must be addressed, and establishing specific quality goals and objectives to be achieved. This comprehensive planning process helps ensure that the overall project scope, detailed drawings, and technical specifications are well-defined and unambiguous. This clarity is a prerequisite for maintaining high-quality construction processes and workflows throughout the project lifecycle. (Akinradewo et al., 2019).

In complex infrastructure projects where multiple stakeholders and intricate interdependencies are involved, comprehensive quality planning is vital for coordinating processes and ensuring collaboration. Effective planning establishes clear goals, defines critical quality characteristics, and maps workflows and control measures. However, in the JSWP, quality planning has often been insufficiently executed, as evidenced by numerous cases of work commencement without obtaining mandatory approvals. This lack of adherence to project quality procedures highlights a significant gap in ensuring consistency and alignment in the project's quality management efforts.

1.13.4 Quality Assurance

Quality assurance is a critical component of effective QMS in the construction industry. It involves implementing a comprehensive set of planned and systematic activities to ensure the constructed facility or infrastructure meets the specified requirements and customer expectations (Juran & Joseph, 2012). Quality assurance encompasses various activities, including inspection, testing, auditing, and monitoring, verifying that the construction processes and materials conform to established standards and specifications. However, in the JSWP, gaps in quality assurance practices have been observed, such as inconsistent inspection routines and inadequate adherence to ITP, often due to the high volume of concurrent projects and strained supervisory capacity. These shortcomings have led to instances where quality issues were only identified after significant work was completed, resulting in rework and delays. By addressing such gaps and implementing robust quality assurance measures, construction projects can enhance the overall quality, reliability, and longevity of the constructed facilities, ultimately meeting or exceeding client requirements and expectations.

1.13.5 Quality Improvement

As per Juran & Joseph (2012) quality improvement targets two main areas: enhancing product features and reducing deficiencies. Improving product features increases customer satisfaction by introducing innovative designs, sustainable materials, or advanced construction techniques. Reducing deficiencies minimizes waste, rework, and delays, thus boosting efficiency.

In JSWP, the lack of a structured approach to continuous quality improvement has often led to repeated deficiencies, such as material waste and recurring design modifications, due to inadequate coordination, especially with other utilities' providers, and poor communication among stakeholders. These recurring issues highlight the importance of adopting principles like a customer focus to meet stakeholder needs, continuous improvement through regular assessments, employee involvement in problem-solving, and a process approach that optimizes each project phase. Addressing these gaps and embracing proactive quality improvement measures early during the planning stage and before issue the projects for bidding, JSWP can enhance efficiency, reduce waste, and deliver high-quality outcomes that meet or exceed client expectations.

1.14 The Role of Artificial Intelligence in Quality Management

Artificial intelligence has emerged as a promising solution to address the complexities and challenges faced while implementing effective quality management systems in the construction industry. AI-powered technologies offer a range of capabilities that can streamline quality management processes and enhance project outcomes. Some studies identified some drivers for AI adoption such as cost, time, performance and customer satisfaction, which are directly related to project outcomes (Yang et al., 2019). Other studies listed some possible benefits of AI such as automating inspections and improving accuracy to leveraging predictive analytics to identify potential issues, AI aligns well with quality management principles and can help construction organizations overcome the inherent difficulties in implementing robust quality management systems (Cubric, 2020).

Recent studies have highlighted several ways AI can enhance quality management in construction. Key technologies like Building Information Modelling (BIM), augmented reality (AR), Internet of Things (IoT), and computer vision (CV) are being integrated into CQM processes (Abioye et al., 2021). AI's success in optimizing manufacturing, healthcare, and finance processes offers strong evidence of its transformative power across industries. Therefore, AI has a high potential in the construction industry by demonstrating how AI can automate inspection processes, identify potential issues, and improve decision-making (Datta, S. D et al., 2024; Nagireddy, 2023).

The case study by Makaula et. al. (2021) highlights the transformative potential of AI in construction project management through the development of a framework that integrates AI technologies across various phases of the project lifecycle. It emphasizes AI's role in enhancing planning, design, execution, and material sourcing while addressing critical aspects such as labor productivity and risk management. This framework is particularly relevant to the current study, as it provides a structured approach to apply AI in construction quality management, emphasizing how AI can optimize processes, improve decision-making, and mitigate project risks. Also, the study identifies key challenges to AI adoption, such as high costs and resistance for job security concerns, which align with barriers faced in the Saudi construction industry.

In the context of JSWP, similar challenges are encountered across the program's large-scale and complex projects. The phased nature of JSWP, coupled with recurring issues in quality planning, inspection, and material management, underscores the need for an AI-driven framework to address inefficiencies. By leveraging AI tools to streamline workflows, enhance compliance monitoring, and proactively manage risks, JSWP can achieve better project outcomes while aligning with Saudi Vision 2030's goals for innovation and sustainability.

However, the construction industry faces persistent challenges in adopting digital technologies. Issues like low productivity, frequent rework, and cost overruns (Pan & Zhang, 2021) highlight the lag in digitalization and the untapped potential of AI. By integrating AI as a moderating variable in quality management practices, construction projects can achieve more consistent and reliable quality outcomes, meeting the industry's evolving demands and paving the way for sustainable advancements.

This study investigates the impact and outcomes of AI-driven technologies, including automation and predictive analytics, on construction quality management. Prominent AI platforms such as Google ML, Microsoft Azure, and IBM Watson offer relevant AI-powered solutions that merit further exploration and analysis within this research context. These platforms offer AI Technology, such ML and NLP, which can support transformative construction quality management practices.

1.14.1 Automation of Quality Processes

One of the key areas where AI can enhance quality management in construction is through automated quality control and inspection. AI-powered computer vision and machine learning algorithms can be leveraged for automated quality inspections, detecting defects, and monitoring construction progress (Regona et al., 2022). AI technology improves the accuracy and consistency of inspections and reduces manual effort and time required, enabling construction teams to identify and address quality issues proactively. For example, AI-driven visual inspection systems can analyze site photographs or video footage to identify deviations from design specifications, detect structural defects, or monitor the installation of building components (Hooda et al., 2021; Luo et al., 2022).

Previous research by Pan & Zhang (2021) has shown that computer vision has increasingly supplanted labor-intensive and often inconsistent visual inspections in evaluating the state of civil infrastructure. This technology enables automated detection of damage, recognition of structural components, identification of unsafe behaviors, and assessment of overall conditions. Such applications of AI in quality control and inspection processes in infrastructure projects can significantly enhance efficiency, accuracy, and timeliness in addressing quality-related issues by facilitating monitoring applications through non-contact methods, capturing a quantitative understanding of infrastructure status, such as estimating strain, displacement, and measuring crack length and width.

1.14.2 Identifying and predicting quality issues

The ability of AI to predict potential quality issues is a transformative application in construction quality management. By analyzing historical project data, real-time sensor inputs, environmental factors, and supply chain disruptions, AI-powered predictive models can forecast quality problems such as delays, cost overruns, defects, or equipment failures (Abioye et al., 2021). For instance, machine learning techniques, as demonstrated in recent research by Dip Datta et al. (2024), have proven effective in identifying construction risks by considering factors like project complexity, weather conditions, and supply chain uncertainties.

Additionally, AI can support informed decision-making in quality management by providing predictive insights and actionable recommendations. By processing vast amounts of data from past projects, real-time site conditions, and process information, AI systems can identify trends, suggest optimal actions, and highlight areas of concern. Similarly, findings by Sota (2017) on AI in construction planning emphasize the potential of AI-driven tools to optimize planning processes by analyzing historical data, forecasting risks, and automating decision-making to improve project outcomes. These capabilities align with the principles of Quality Planning, which focus on defining objectives, allocating resources, and identifying potential risks to prevent defects. The integration of AI's decision-support systems enables project teams to make more accurate and timely decisions, improving resource allocation, reducing inefficiencies, and enhancing overall project quality (Dabous et al., 2023).

For large-scale Programs like JSWP, AI's predictive capabilities are instrumental in tackling persistent issues such as utility conflicts, material issues, non-compliance to procedures, and project delays. By analyzing historical and real-time data and utilizing predictive analytics, AI empowers project teams to foresee potential risks and implement solutions before problems arise. This preventive approach reduces the likelihood of rework, minimizes disruptions, and cut additional costs. Furthermore, AI enhances coordination across the program's numerous sites, ensuring smoother workflows and higher-quality outcomes. Incorporating AI-powered predictive tools into quality management practices allows construction projects to achieve their quality objectives more effectively, leading to improved performance greater project success and customer satisfaction.

1.14.3 Improving the efficiency of quality management processes

AI-powered technologies can also enhance the efficiency and effectiveness of quality management in construction by automating routine tasks, streamlining data collection and analysis, and optimizing quality control workflows. AI techniques can also generate valuable insights into the complex construction process. This knowledge is critical to project success and can guide the optimization of the construction execution process, helping to make the project run more smoothly and efficiently (Pan & Zhang, 2021). For instance, AI-driven natural language processing can automate the extraction and analysis of quality-related information from project documentation, such as inspection reports, checklists, and requests for information.

Another way to enhance construction quality management processes is by integrating artificial intelligence with existing quality management tools and methodologies, such as Failure Mode and Effects Analysis (FMEA), Statistical Process Control (SPC), and Lean Quality Management Systems, to improve their effectiveness (Yang et al., 2019). AI-based Integrated Quality Management Information System (IQMIS) proposed by Yang et al. (2019) enables real-time data acquisition, predictive modeling, and intelligent decision-making across quality planning, control, and improvement. For example, AI can link FMEA data with IoT devices or other systems to better manage, monitor, and optimize quality-related processes throughout the construction lifecycle. These innovations allow established QMS to proactively identify and address quality risks, reduce inefficiencies, and improve overall project outcomes.

The reliance on traditional inspection methods in JSWP poses significant challenges in managing quality across the program's large and complex projects. With numerous dispersed sites, high volumes of activities, and intricate interdependencies, traditional approaches often fail to provide the scalability and real-time responsiveness needed to ensure consistent quality. These limitations result in delayed identification of defects, inefficient allocation of resources, increased rework, and increased extension of time requests. Integrating AI technologies into the quality management process can bridge these gaps by automating inspections, analyzing data in real-time, and predicting potential quality issues before they escalate. By transitioning from reactive to proactive quality management, AI can enhance the efficiency and effectiveness of CQM practices, ensuring better outcomes for large-scale and complex infrastructure projects.

1.14.4 Challenges for Adopting AI in CQM

A recent pilot survey conducted to explore the adoption of artificial intelligence in Saudi Arabia's construction industry provides valuable insights into the sector's awareness, readiness, and challenges regarding AI integration. The survey revealed a range of barriers, including limited technical expertise, insufficient data quality, and resistance to change, as well as concerns over job displacement and high implementation costs. Additionally, regulatory uncertainties and the lack of clear frameworks for AI adoption were highlighted as significant hurdles.

These findings offer a snapshot of the industry's current landscape and emphasize the need for targeted strategies to address both technical and organizational challenges. These insights are particularly relevant to this study, as they underscore the importance of preparing the industry for AI-driven solutions.

While the potential benefits of AI in construction quality management are significant, there are also several challenges and barriers to widespread adoption. Adopting AI-powered technologies in construction quality management contexts can be improved by factors such as the industry's traditional resistance to change, concerns over data privacy and security, the need for upfront investment in new technologies, and AI-specific skills and expertise among construction professionals. (Regona *et al.*, 2022).

1.14.4a Cultural, Social, and Organizational Challenges

The lack of adherence to organizational QMS and established CQM practices poses significant barriers to successfully integrating AI technologies in the construction industry. This challenge is particularly evident in JSWP, where frequent non-compliance with quality procedures undermines effectiveness of QMS. Similar challenges are observed in studies like Khan et al. (2019), which identified insufficient adherence to QMS standards, lack of training, and inconsistent enforcement of quality protocols as critical obstacles. These issues are further exacerbated by cultural & organizational resistance to change, coupled with a lack of commitment to quality, which disrupts the implementation of structured quality processes.

Moreover, social and organizational challenges significantly hinder the adoption of AI-driven quality management practices in the construction industry. Concerns about job security, resistance to change, and the steep learning curve associated with new technologies are prevalent among construction professionals (Regona et. al., 2022). The Saudi construction industry remains deeply rooted in traditional practices, where quality management systems are often not perceived as a strategic priority. Aichouni et al. (2014) emphasized similar challenges in their study on the *Hail* region, where insufficient training, lack of top management commitment to quality, and organizational resistance were identified as critical barriers to the effective implementation of quality management systems. These challenges have perpetuated widespread non-adherence to QMS practices, further limiting the industry's ability to adopt advanced AI-driven quality solutions.

Many organizations, including JSWP, view quality management as an additional administrative burden that increases costs and delays work progress rather than as an essential investment for achieving long-term success. This mindset perpetuates a cycle of low adoption of modern quality management frameworks, making it difficult for companies to recognize the significant benefits these systems can bring, such as enhanced efficiency, reduced rework, improved customer satisfaction, and better reputational standing within the industry (Quadri et. al. 2021).

AI technologies depend on structured and reliable processes to deliver meaningful insights and operational benefits. However, foundational gaps in quality management, combined with social and cultural barriers, result in flawed data and workflows that diminish the value of AI applications (Westenberger et al., 2021). These challenges align closely with the first research question, which examines how CQM practices become insufficient in addressing the complexities of large-scale infrastructure projects. Without addressing foundational gaps in quality culture, such as ensuring adherence to standards and fostering accountability, AI solutions are unlikely to deliver their intended benefits. This highlights the urgent need for management intervention to instill a robust quality culture within the organization.

1.14.4b Integration with Existing Systems

Integrating AI systems with existing quality management processes can be complex and often requires high technical expertise. Successful integration demands careful planning to ensure that AI tools complement existing workflows rather than disrupt them. This challenge is particularly evident in construction projects, where established procedures and legacy systems may need to be adapted or updated to accommodate new AI-driven approaches (Na et al., 2023; Jäkel et al., 2022).

1.14.4c Data Quality and Availability

The effectiveness of AI technologies in construction heavily depends on the quality and availability of data and the expertise of professionals managing these systems. Reliable and relevant data are essential for training AI models to provide accurate predictions and insights. However, construction projects often face challenges such as data variability, incomplete records, and inconsistent data collection practices, which can hinder the development of robust AI applications or the integration with current systems (Castronuevo & Arboleda, 2024; Kelepouris, 2023).

1.14.4d Skill Gap

The skill gap presents a significant barrier to AI adoption in the construction industry, with a shortage of trained professionals limiting the ability to develop, implement, and manage AI systems effectively (Castronuevo & Arboleda, 2024). This challenge is further compounded by organizational issues, including insufficient stakeholder alignment, trust and resistance to change, which hinder the seamless integration of AI

technologies (Cubric, 2020). In the context of JSWP, these barriers are particularly evident, as the program relies on fragmented quality management frameworks and traditional methods. Bridging the skill gap requires substantial investment in targeted training and education programs to equip personnel with the expertise needed to leverage AI technologies effectively. Addressing these foundational requirements, including high-quality data and skilled expertise, and management support is essential for successfully integrating AI into Construction CQM practices and achieving improved project outcomes.

1.14.4e Ethical Considerations

Nagireddy (2023) and Cubric (2020) indicated that using AI in various business sectors, including construction, raises important ethical considerations that must be carefully addressed. Issues such as trust, data privacy, algorithmic bias, and the potential displacement of human workers by non-human system, are critical concerns that must be proactively managed. For example, ensuring the protection of sensitive project data and mitigating biases in AI-powered decision-making processes are essential to maintain trust and fairness in AI applications.

Additionally, the potential impact of AI on construction workers, such as job automation, should be considered and balanced with the need for technological advancements. Adopting a human-centered approach that prioritizes ethical principles, such as transparency, accountability, and employee well-being, is crucial for AI's successful and responsible integration in construction quality management. Careful consideration of these ethical factors will help foster trust, acceptance, and the equitable deployment of AI-driven solutions in the industry (Abioye et al., 2021).

1.14.4f Cost of AI integration

The benefits of AI-driven solutions in the construction industry are indisputable. Several researchers, including Luca et al. (2022), Abioye et al. (2021), and Sota (2017), found that the initial investment and ongoing maintenance costs of AI-driven solutions, such as robotics or CV can be prohibitively high, particularly for small-scale subcontractors and firms that comprise a significant portion of the construction industry. This poses a significant barrier to the widespread adoption of these technologies. Therefore, Luca et al. (2022) discussed deeper the cost-benefit challenge

of AI adoption and emphasized the need for construction companies to invest in data collection and processing technologies to utilize AI effectively. They also pointed out that companies should focus on clear target areas for AI implementation rather than simply adopting the latest technology trends without a precise cost-benefit analysis. This suggests that the initial cost of AI and the associated data infrastructure is challenging for broader AI adoption in the construction industry.

Construction companies will face additional challenges when traditional and manual construction quality management practices are already in place, which is the case in JSWP. Integrating AI-driven solutions will require significant changes to existing processes and workflows, and construction firms may be reluctant to abandon their established quality management approaches, even if AI offers potential benefits. Cubric (2020) suggested the use of hybrid solutions combining AI and non-AI systems. Overcoming this resistance to change and ensuring a smooth transition to AI-enabled CQM will be a critical challenge that construction companies must address.

This study argues that integrating artificial intelligence in construction quality management holds significant potential to enhance project outcomes. Nevertheless, researchers have identified that addressing the challenges associated with AI adoption is essential to fully realizing its benefits. Investing in training and education, establishing industry standards, and proactively tackling ethical considerations will be pivotal to successfully integrating AI-driven solutions in the construction industry.

1.15 Construction Projects outcomes

Various factors, including project management practices, resource availability, environmental conditions, stakeholder involvement, and organizational culture, influence construction project outcomes. Most research studies conclude that key project outcomes in construction are typically evaluated using the Iron Triangle of Project Management, encompassing cost, schedule, and quality, along with additional factors such as scope, safety, customer satisfaction, environmental compliance, and legal adherence (Teshome & Gobana, 2018; Leong et al., 2014). These metrics are broadly recognized as vital indicators of project success, offering a holistic assessment of a project's performance and alignment with stakeholder expectations and prevailing industry standards.

1.15.1 Cost

Cost is a fundamental measure of construction project success. Effective cost management, including accurate budgeting, cost control, and efficient resource utilization, is crucial for ensuring projects are completed within the allocated budget (Leong et al., 2014). Previous studies have highlighted the significant impact of cost overruns on project profitability, client satisfaction, and the overall viability of construction firms. Also explored the negative impacts of cost overruns on various aspects of construction projects. Neyestani, B. (2016) concluded on his research that effective QMS can positively impact time performance and cost control, leading to better project outcomes.

While high-quality design might initially increase costs, ensuring conformance to quality standards during construction can lead to long-term cost savings. On the other hand, poor-quality construction can result in significant long-term problems, including structural issues, safety hazards, and costly repairs (Tang et al., 2005.). Similarly, robust quality management practices, like AI-Driven, require upfront investment, but the costs of rework and remedying defects often exceed these expenses. The study by Ali et. al. (2010) emphasizes the importance of prevention, appraisal, and failure costs in improving project outcomes but notes significant barriers, such as poor knowledge and limited resources, which hinder effective implementation. Additionally, poor quality can undermine customer satisfaction, damage a company's reputation, and lead to legal liabilities. Ultimately, the long-term consequences of substandard quality outweigh any short-term cost savings, emphasizing the critical importance of effective quality management in construction projects.

1.15.2 Schedule

Timely project delivery is another crucial measure of construction project success. Time performance evaluates the project's adherence to its planned Schedule. Delays in construction projects can lead to significant financial losses, missed business opportunities, and reputational damage for construction firms. The study by Hwang and Yang (2014) highlights rework as a major contributor to project delays, with its root causes often tied to quality-related issues such as design errors, inadequate quality control, and poor adherence to project specifications. The research underscores the importance of proactive quality management in minimizing rework, noting that early

identification and resolution of potential quality issues can significantly reduce disruptions and improve project schedules. By addressing rework at its root, through robust quality assurance and control practices, construction projects can enhance efficiency and achieve better outcomes.

Low & Ong (2014) suggest that integrating quality management practices, such as comprehensive quality planning, quality assurance, and quality control, can help mitigate schedule delays and improve overall time performance in construction projects. For JSWP, adopting robust quality management practices would provide a more structured approach to addressing quality-related inefficiencies. By emphasizing quality planning and assurance, the program could proactively identify and mitigate risks that contribute to delays, ultimately improving time performance across its large and complex infrastructure project.

The survey conducted by Assaf & Al-Hejji (2006) identified numerous factors contributing to schedule delays in the construction industry in Saudi Arabia, including poor planning, ineffective subcontractor management, material shortages, adverse weather conditions, and change orders. Similar issues have been observed in JSWP, particularly poor planning and delayed design approvals, which exacerbate schedule delays across the program's dispersed and concurrent projects. Additionally, poor quality, defects, and reworks further compound these delays, disrupting workflows and increasing the time required to complete projects.

The studies discussed highlight rework as a significant contributor to project delays, often stemming from quality-related issues such as design errors, inadequate quality control, and poor compliance with project specifications. These findings emphasize the critical need for proactive quality management practices, as rework not only disrupts workflows but also escalates costs and prolongs schedules. In the context of JSWP, rework is particularly impactful given the program's scale and complexity. Issues such as delayed design approvals and non-compliance with quality plans exacerbate schedule delays, creating ripple effects across the program's dispersed and concurrent projects. Addressing these challenges requires robust quality assurance and control practices that prevent rework by ensuring adherence to specifications and early detection of quality issues, ultimately improving time performance.

1.15.3 Quality

Quality is one of the three dimensions of the Iron Triangle and serves as a critical measure of construction project success. In the context of construction, quality refers to the conformance of the final product or service to specified requirements, standards, and client expectations. This definition aligns with the principles of Philip Crosby, who emphasized that "quality is conformance to requirements." Quality performance is assessed by evaluating the quality of workmanship, materials, and adherence to established specifications and standards, ensuring that the constructed facility meets or exceeds stakeholder expectations (Crosby, 1980).

Poor quality in construction can have far-reaching consequences, including structural failures, safety hazards, client dissatisfaction, and legal liabilities. The construction industry has long struggled with quality issues, and research suggests that most quality-related problems are attributed to the human factor, particularly a need for more professional ethics and commitment to quality for all stakeholders involved in the project (Aziz, 2013). To address this challenge, construction firms have increasingly adopted various quality management frameworks, such as Total Quality Management, Six Sigma, and Lean Construction, to improve quality assurance and control throughout the project lifecycle.

However, the adoption of quality management frameworks has faced significant challenges in the construction industry. Despite the potential benefits, construction firms need help effectively implement and sustain these practices throughout the project lifecycle. Lack of employee buy-in, resistance to change, and the complex, fragmented nature of construction projects has hindered the widespread adoption and success of these quality management initiatives (Aichouni et al., 2014) (Srdoč et al., 2005). Moreover, the construction industry's traditional focus on time and cost, often at the expense of quality, has contributed to the persistent quality issues faced by the sector (Jraisat et al., 2016).

In the context of the Jeddah Stormwater Program, the expansion of projects in size and complexity has led to a noticeable rise in the number of Site Observation Reports (SORs) and Non-Conformance Reports (NCRs). These reports highlight recurring

issues such as deviations from approved designs, inadequate compliance with quality standards, material issues, non-adherence to quality plan, and defects arising during construction. The growing volume of SORs and NCRs underscores the challenges of maintaining consistent quality control across a program of this scale, further emphasizing the need for more efficient and proactive quality management practices. Integrating AI-driven technologies could help reduce such occurrences by automating compliance checks, enhancing real-time monitoring, and identifying potential quality issues before they escalate. This would provide a systematic approach to managing quality in large-scale infrastructure projects like JSWP.

1.15.4 Customer Satisfaction

Customer satisfaction is an essential measure of construction project success, as it reflects the extent to which the client's expectations and requirements are met. This is particularly important in the construction industry, where projects are often highly customized and tailored to the client's needs.

Various factors influence customer satisfaction, including the quality of the final product, the timeliness of project delivery, and overall responsiveness and communication throughout the construction process. In the construction industry, client satisfaction is a multidimensional concept encompassing various aspects, such as project delivery, quality of workmanship, timeliness, responsiveness to issues, and overall project experience (Alshihre et al., 2020). Achieving high levels of customer satisfaction is crucial for construction firms, as it can lead to repeat business, positive word-of-mouth referrals, and improved reputation within the industry. Moreover, satisfied clients are more likely to be willing to engage in collaborative partnerships and support future projects, which can be particularly beneficial in the highly competitive construction market (Ramlee et al., 2016).

Conclusion of Literature

The literature highlights several methods for measuring construction project outcomes, focusing on traditional metrics and the potential for AI to enhance measurement accuracy and efficiency (Leong et al., 2014). AI-powered technologies offer transformative opportunities in quality management, such as automating inspections,

predicting quality issues, and improving workflow efficiency. However, existing quality research often applies AI to isolated aspects of quality management or specific project outcomes, without addressing its holistic, systematic impact on overall CQM practices (Dabous et al., 2023).

The literature Table (1-1) at the end of this chapter provides a structured review of key themes in the study. The first section examines the challenges associated with traditional CQM practices, particularly in large and complex projects, highlighting recurring issues such as non-compliance with quality standards, defect detection, and rework management, which are prevalent in infrastructure projects. Numerous case studies within this section provide valuable insights into these challenges, reinforcing the widespread nature of these problems across various contexts.

The second section focuses on the intersection of Quality Management and Artificial Intelligence. This review identifies a notable gap in existing literature, where studies primarily focus on isolated applications, such as predictive analytics or defect detection, without exploring AI's systemic impact on CQM as an integrated framework. Moreover, there is a lack of case studies examining the practical implementation of AI in enhancing CQM practices. This gap highlights the need for further investigation into AI's role in optimizing quality planning, control, assurance, and improvement.

The third section explores AI applications in construction and project management, emphasizing its ability to optimize specific outcomes, such as cost or schedule performance. However, these studies often overlook AI's broader potential to revolutionize quality management practices holistically. Together, these insights underline the necessity for a comprehensive investigation into AI's transformative role in CQM, which this study aims to address. By focusing on the Jeddah Stormwater Program as a case study, this research seeks to bridge this gap and offer a novel contribution to the field.

Table (1-1) Literature Review Summary Table

No	Title	Author	Year	Literature Summary	Researcher Comments and relevance to JSWP
A	Literature related to Quality Management and Project / Construction management - Challenges of Traditional CQM Practices				
A01	Quality management at construction projects case study of stormwater network project (Case Study - UAE)	Hamdan	2024	This paper highlights the implementation of quality management systems in stormwater network projects. It emphasizes the importance of strict adherence to QMS processes during all stages of work to prevent defects, ensure compliance, and reduce rework. Specific examples of quality violations and corrective actions are provided from the conducted case study.	The paper provides valuable insights into quality management challenges and corrective measures in a stormwater context, offering parallels to JSWP's recurring quality issues such as MOS, ITP and shop drawings, and opportunities for AI-driven solutions.
A02	Quality Assurance and Quality Control for Project Effectiveness in Construction and Management	Salvi & Kerkar	2020	The paper examines the importance of QA and QC in enhancing project effectiveness within the construction industry. The study emphasizes that defects or failures in constructed facilities can lead to increased costs and delays, making QA/QC crucial for ensuring uniformity and compliance with specifications. The authors outline the methods of implementing QA/QC processes, such as inspections, documentation, and adherence to standards, highlighting how these measures can improve project quality and reduce costs over the project lifecycle	This paper provides valuable insights into how QA and QC practices contribute to project outcomes such as cost efficiency, quality consistency, and stakeholder satisfaction , which are key areas of focus of the thesis on quality management's impact on construction project outcomes. The paper also outlined the challenges and benefits of QA/QC integration, offering context on how these practices might be further enhanced through AI technologies in complex projects like the Jeddah Stormwater Program.
A03	Evaluation of Quality during construction projects (Case study – Pakistan)	Khan et. al	2019	In this study, the authors Identifies major challenges in QMS implementation, including insufficient adherence to standards, lack of training, and inconsistent enforcement. Cultural & organizational resistance further hinders adoption.	Highlights non-compliance with existing CQM practices, similar to JSWP, emphasizing the need to address foundational issues before integrating AI into quality management systems.
A04	Framework to Enhance the Implementation of Quality Management System in Construction (Case Study – Malaysia)	Othman et. al	2018	The study Identifies challenges in implementing QMS in high rise construction, including limited QA/QC knowledge, poor worker attitudes, high material waste, and excessive QA/QC workloads. Proposes a framework emphasizing management commitment and resource optimization.	The authors Highlight similar challenges with JSWP, such as non-compliance to quality procedures and inefficiencies in supervision. Provides a foundational framework to complement AI-driven CQM solutions for large infrastructure projects.
A05	Critical Success Factors in Infrastructure Projects: A Case Study of Flood Mitigation (Case Study – Malaysia)	Zakaria et al	2017	In this study, the authors identify critical success factors for infrastructure projects “Stormwater” like planning, stakeholder coordination, and adherence to master plans in flood mitigation projects. Highlights resource allocation and compliance as barriers.	The study Offers insights into JSWP challenges by emphasizing planning, compliance, and coordination gaps, which challenge traditional CQM practices and support the demand for AI integration in CQM.

No	Title	Author	Year	Literature Summary	Researcher Comments and relevance to JSWP
A06	Quality in construction management: an exploratory study	Jraisat et al.	2016	This paper investigated the factors that affect quality in construction. It highlighted the construction industry's focus on cost and time at the expense of quality, leading to persistent issues.	The paper found that the major factors affecting quality in construction are human resource management, customer satisfaction, and construction related issues.
A07	Effectiveness of Quality Management System (QMS) on Construction Projects	Neyestani	2016	This paper evaluated the impact of QMS implementation in construction projects. It found that QMS can affect customer satisfaction, cost, time, and quality. The findings emphasize that QMS implementation enhances project outcomes by systematically improving management processes. AI can further improve decision-making by providing data-driven insights, predictive analytics, and real-time feedback loops	Although the paper investigates the broader effects of QMS, including customer satisfaction and operational efficiencies, it particularly notes that QMS least affects the project scope or quality compared to other factors. This gap suggests that while QMS frameworks (like ISO 9001) standardize processes, there might be room for enhancing their direct impact on quality, which is where AI could play a transformative role and can be integrated into QMS to amplify its effectiveness, especially quality management.
A08	Rework and schedule performance: A profile of incidence, impact, causes and solutions	Hwang & Yang	2014	This paper investigated the effect of reworks on projects. It was found that rework is a significant factor in schedule delays with a high occurrence rate. Root causes of reworks include design changes and poor design coordination.	Rework often arises from inadequate planning and poor coordination among stakeholders, compounded by frequent non-compliance with procedures, delays in Method Statements (MOS), and shop-drawing approvals caused by change orders. The study explores the impact of rework on both schedule and cost, highlighting its disruptive effects on project performance. Integrating AI into quality management systems could help minimize rework and enhance schedule adherence. By automating elements of the change management process and utilizing predictive analytics, AI could proactively identify potential schedule or budget overruns related to rework and mitigate their impact.
A09	The Degree of Using Methods of Quality Management in the Implementation of Construction Projects in Jordan	Khatatbeh, Ahmed	2014	The study highlighted varying levels of implementation of CQM practices in the construction industry in Jordan. The study listed the most significant problems that hinder the application of CQM practices such as management commitment, effective communication between stakeholders, lack of staff training and others. The challenges impact on the ability of construction companies to meet the required quality and customer's needs.	The result of the study aligns with JSWP challenges, such as non-compliance with quality protocols and weak organizational alignment, lack of adequate supervision, stakeholders' coordination, emphasizing the need for foundational improvements to enable AI integration in CQM.

No	Title	Author	Year	Literature Summary	Researcher Comments and relevance to JSWP
A10	An empirical study of quality management systems in the Saudi construction industry (Case Study – KSA)	Aichouni et al.	2014	The study highlights significant challenges in implementing Quality Management Systems (QMS) in the Saudi construction industry in Hail Region, focusing on insufficient training, lack of top management commitment, and organizational resistance. These issues result in widespread non-adherence to QMS strategies, tools, and techniques, particularly in the Hail region.	This study emphasizes how foundational gaps in QMS implementation, such as poor adherence to quality processes and organizational resistance, make the adoption of advanced AI-driven solutions even more challenging. This is directly applicable to JSWP, where similar non-compliance and adherence issues exacerbate the complexity of integrating AI technologies.
A11	Project Quality Management Critical Success Factors for Buildings (IMP)	Low, S. P., & Ong, J	2014	This book explores how effective quality management practices influence the success of projects. The authors identify critical success factors such as leadership commitment, stakeholder engagement, continuous improvement, and adherence to standards. Using case studies, they illustrate strategies for integrating quality management systems, emphasizing customer satisfaction and risk.	The author emphasizes leadership, stakeholder engagement, continuous improvement, and adherence to standards directly ties into the core areas of Quality Planning, Quality Control, Quality Assurance, and Quality Improvement . Also, his perspective for examining how structured quality practices impact project outcomes such as cost, schedule, quality, and customer satisfaction goes well with the aim of the thesis
A12	Study of Quality Management in Construction projects	Chin Keng, Hamzah	2011	The article highlights that quality management should be intertwined with all operational and managerial processes within a construction company. It emphasizes the need for a strong management commitment to quality, the implementation of appropriate quality management practices, and addressing the challenges that hinder effective quality management in construction projects	The findings of this paper highlighted the importance of quality management in construction projects. The author highlighted that quality management in construction is not stand alone management, which support the importance of CQM practices as it the role of every one on the project.
A13	Quality Cost in the Construction Industry – Preliminary Findings in Malaysia (Case Study – Malaysia)	Ali, et. al.	2010	Explores the awareness and application of Cost of Quality (COQ) principles in construction. Highlight challenges such as poor knowledge, limited resources, focus on short-term profits over preventive measures. Suggests COQ as performance indicator for continual improvement to ISO9001	The study emphasizes COQ as a tool to address JSWP challenges by reducing costs and inefficiencies. Proposes leveraging AI to optimize COQ processes, enhance resource allocation, and minimize rework.
A14	Factors Affecting the Performance Of Construction Projects In The Gaza Strip (Case Study – Gaza)	Enshassi et al.	2009	The paper identifies several key factors impacting construction project performance in the Gaza Strip, including delays due to border and road closures leading to material shortages, unavailability of resources, escalation of material prices, and the lack of experienced personnel. These issues highlight the complex interplay between external economic and political conditions and internal project management challenges.	the paper does not specifically focus on AI, the challenges it outlines—like resource availability, material cost escalation, and effective project leadership—can be mitigated through AI technologies. AI can predict material shortages or optimize resource allocation, enhancing project performance. conformance to specifications and quality of equipment and materials. AI tools can enhance quality assurance processes, ensuring compliance and improving the overall material management system. This approach is part of the objectives of this research.

No	Title	Author	Year	Literature Summary	Researcher Comments and relevance to JSWP
A15	A Case Study on Quality Management System in Construction Project (KLIA) (Case Study – Malaysia)	Abdullah et. al.	2008	Highlights challenges in implementing QMS for the Kuala Lumpur International Airport project (KLIA), including integrating PQPs, stakeholder coordination, and compliance with statutory and project-specific standards. Emphasizes the importance of structured approaches like inspections, testing, and audits.	The study's emphasis on auditing, inspection, and testing aligns with the JSWP's identified needs. For example, KLIA's method of integrating inspection and testing plans (ITP) into PQPs can be highlighted as a best practice that JSWP could adopt, especially when integrated with AI technologies to automate and monitor compliance in real-time. It also mirrors JSWP's challenges in managing compliance and coordination across dispersed projects. Suggests AI as a tool to automate monitoring and enhance compliance management.
A16	The Role of Culture as Driver of Quality Management and Performance: Infrastructure Versus Core Quality Practices	Naor et al.	2008	The study investigated the relationships between organizational culture, infrastructure, core quality management practice, and the link to performance. It provides an insightful exploration of how organizational culture influences quality management practices and overall performance. The study distinguishes between infrastructure and core quality management practices and analyzes their interactions with organizational culture in the context of manufacturing performance.	These findings can be directly relevant to this research by illustrating the crucial role of cultural factors in the implementation and effectiveness of quality management practices in construction projects. The research can find out how similar dynamics apply within the Jeddah Stormwater Program and other construction contexts, particularly how AI can be integrated to enhance these interactions and outcomes.
A17	Quality Assurance and Control in the Construction of Infrastructure Services in Developing Countries (Case Study – Pakistan)	Khan et al.	2008	The authors examined the challenges and implementation of quality assurance & quality control practices in construction. The study highlights the importance of CQM practices and to apply it, including lack of clear specifications, limited stakeholder awareness, and inadequate statistical methods. Highlights the potential of computer-aided tools to enhance QA/QC processes.	This study Highlights similar CQM challenges in JSWP, that are also affected by the size and complexity of construction projects, emphasizing the need for AI-driven solutions to improve compliance and efficiency of CQM practices.
A18	Causes of delays in large construction projects (Case study – KSA)	Assaf & Al-Hejji	2006	The author conducted a survey on time performance of different types of construction projects in Sadu Arabia. The survey aimed to find out the cause of delay in construction. It found that average of 10% to 30% of deviation from original schedule. 70% of projects had overrun, and the major cause was changing orders.	The author identified poor planning, ineffective subcontractor management, and material shortages as significant challenges to quality management. All these issues directly related to current challenges we are facing at JSWP

B	Literature related to Quality Management and Artificial Intelligence – AI in Enhancing Quality management				
No	Title	Author	Year	Literature Summary	Researcher Comments and relevance to JSWP
B01	A Literature Review of Artificial Intelligence in Asphalt Quality Assurance (Case Study)	Ryan B. Castronuevo Edwin R. Arboleda	2024	Reviews AI applications in asphalt quality assurance, highlighting intelligent sensing aggregates, machine learning for defect detection, and dynamic monitoring systems. These innovations enhance quality evaluation, decision-making, and material optimization.	This study provides a relevant example of how AI-driven quality management systems can improve construction project outcomes. It can provide a model for integrating AI into quality management processes in large-scale projects. For JSWP, AI could enhance compliance monitoring, automate quality checks, and proactively address defects. The study also highlights challenges related to data availability and model interpretability, offering insights into potential limitations and considerations when adopting AI-driven solutions in complex construction projects.
B02	Editorial: Automation and artificial intelligence in construction and management of civil infrastructure	<i>Dabous et al.</i>	2023	discusses the increasing trend of automation and AI adoption in the construction industry. It highlights the slower pace of adopting new technologies in construction compared to other sectors due to the industry's complexity.	This Demonstrated the use of predictive analytics to identify and mitigate quality risks, such as delays and cost overruns. The author emphasizes the need for more research to understand the potential of AI and automation in addressing construction and management challenges, which is in light with the focus of the current research
B03	Digital technology for quality management in construction: A review and future research directions	Luo et al.	2022	The research investigated digital- technology that can be used to enhance CQM. Results found enhancement in detecting concealed works and preventive and post-completed defects.	This paper focuses on digital technologies in quality management, including use of AI. It provides a clear connection between digital technology apps and the enhancement of quality management processes illustrating both current capabilities and gaps in technology application within the scope of construction quality management, highlighting opportunities, but not relating those benefits to project outcomes.
B04	Failure of AI Projects: Understanding the Critical Factors	Westenberger et. al	2021	The paper Identifies factors contributing to AI project failures, including unrealistic expectations, organizational constraints, and technological challenges like poor data quality and model instability.	Highlight barriers relevant to JSWP, such as resistance to technology, lack of skilled personnel, and data challenges, which must be addressed for successful AI integration in CQM.
B05	Drivers, Barriers, and Social Considerations for AI Adoption in Business and Management	Maria Cubric	2020	The author identifies a significant skill gap in AI adoption due to a lack of trained professionals and discusses organizational challenges, such as resistance to change and insufficient stakeholder alignment.	Highlights the need for addressing skill gaps and organizational barriers in JSWP, emphasizing the importance of training and alignment for AI integration into CQM practices.

No	Title	Author	Year	Literature Summary	Researcher Comments and relevance to JSWP
B06	Artificial Intelligence for Product Quality Inspection toward Smart Industries: Quality Control of Vehicle Non-Conformities	Chouchene et al	2020	The paper discusses the integration of AI within smart factory systems and how it overcomes limitations of manual inspection, such as operator fatigue and inconsistency, by using AI-driven automation and cognitive capabilities. and the use of AI-based vision systems to improve product quality inspection in smart industries, particularly for the detection of non-conformities in vehicles. The proposed system leverages AI, specifically machine vision (MV), to automate defect detection and minimize human error in inspection tasks	The paper shows how AI-driven systems can improve quality inspection processes by enhancing accuracy, reducing errors, and increasing productivity—concepts that can be adapted to the construction industry, particularly for complex infrastructure projects. Automated detection can ensure quality control aligns with the focus on how AI can enhance quality management practices and optimize project outcomes. Insights from this paper can support the exploration of how AI technology can transform traditional quality assurance and control methods into more data-driven, efficient systems.
B07	Quality 4.0—the challenging future of quality engineering	Zonnenshain and Kenett	2020	This paper discusses Quality 4.0 as a contemporary framework for updating traditional quality engineering in response to the Fourth Industrial Revolution. The authors explain that quality models have evolved from inspection, quality control, quality assurance, quality management, and quality by design toward data-driven and integrated quality systems. The paper highlights key Quality 4.0 directions, including data-driven quality, modeling and simulation, prognostics, integrated quality management, maturity assessment, data science, reliability integration, and information quality.	This paper is highly relevant to the current study because it supports the theoretical link between traditional quality management and AI-enabled Construction Quality Management. For JSWP, the study helps explain why traditional CQM practices need to be enhanced through digital technologies, data analytics, integrated platforms, and AI-supported decision-making. It also supports the research argument that AI can act as an operational enhancer within quality governance, especially when supported by data maturity and integrated digital systems.
B07	Essential ingredients for the implementation of Quality 4.0: A narrative review of literature and future directions for research	Sony et al.	2020	This paper investigates the key ingredients required for the effective implementation of Quality 4.0. Through a narrative literature review, the authors identified eight main ingredients: handling big data, improving prescriptive analytics, enabling vertical, horizontal, and end-to-end integration, using Quality 4.0 for strategic advantage, leadership, training, organizational culture, and top management support.	This paper is highly relevant to the current study because it explains why AI-enabled quality management requires more than technology adoption. For JSWP, the findings support the need for executive-level digital quality governance, AI competency development, integrated project data, advanced analytics, and management support to move from traditional CQM toward AI-enhanced CQM and mature digital quality governance.
B08	Imaging Quality Control in the Era of Artificial Intelligence	Larson and Boland	2019	This paper discusses how AI technologies can transform quality control in medical imaging. The authors outline eight key elements essential for comprehensive process control in AI-based imaging systems, emphasize that AI tools alone cannot guarantee consistent quality without integrating these essential process control elements.	This paper might be on the medical field, but the concepts might apply on defect detection on construction projects, especially on material delivery inspection. The idea will need future investigation.

No	Title	Author	Year	Literature Summary	Researcher Comments and relevance to JSWP
B09	Integrating AI Technologies in Quality Management Systems	Yang et al.	2019	The paper tried to discover the connection between QMS and AI tech by exploring how AI enhanced quality tools help in improving predictive analytics can enhance decision-making in quality management processes. A conceptual framework of AI based Information Quality Management System “IQMIS” framework was developed, to enhance QMS functions.	This study is directly applicable to JSWP, as we are trying to understand the effect of AI-enhanced QMS tools such as predictive analytics to monitor ongoing projects and anticipate risks.
B10	Models and Methods for Quality Management based on AI application	Srdoc et al.	2005	The paper presents a comprehensive approach to enhancing quality management through AI-driven techniques by leveraging AI technologies such as text mining, aspect sentiment analysis, and decision tree modeling to evaluate and improve customer satisfaction. The approach emphasizes using big data to monitor and evaluate service quality continuously, thus supporting more dynamic and effective decision-making in quality management.	The paper studied how AI can be leveraged to analyze large volumes of data and transform customer feedback into actionable insights, thereby improving overall project quality and customer satisfaction. It may provide useful frameworks or inspiration for incorporating AI-driven decision support in JSWP. This could help demonstrate how AI tools can enhance data-driven decision-making, using big data tech, i.e. historic data from previous projects.

C Literature related to Artificial Intelligence and Project / Construction Management					
No	Title	Author	Year	Literature Summary	Researcher Comments and relevance to JSWP
C01	Artificial intelligence and machine learning applications in the project lifecycle of the industry: A comprehensive review	Datta, S D et al	2024	The paper thoroughly assesses how AI and ML can be effectively integrated across various phases of a construction project's life cycle. Also, how AI and ML can revolutionize the construction industry by enhancing productivity, reducing cost overruns, improving site safety, and optimizing project management efficiency.	The paper did not mention the use of AI in quality planning during the planning stage of the project. Also, the lack of focused investigation into how AI can enhance quality management practices in construction provides a unique angle for the study.
C02	Artificial Intelligence and Its Impacts on Project Management	Reddy Nagireddy, Sindhu	2023	The paper investigated how AI can be integrated into PM practices, concluding that AI can improve project planning, resource allocation, risk management, and decision-making.	AI tools can improve the accuracy of forecasting, perform repetitive tasks, and enhance decision-making through predictive analytics and data-driven insight. But it did not address the explicit connection between AI technologies and their direct impacts on quality management in construction projects.
C03	A Qualitative Study on Artificial Intelligence and Its Impact on the Project Schedule, Cost and Risk Management Knowledge Areas Presented in PMBOK®	Friðgeirsson et al.	2023	This paper focuses on the impact of AI on PMBOK's area of knowledge, cost, risk, and schedule. The research shows that AI has potential benefits in these areas, particularly where historical data and repeated tasks are involved	The implications of AI in cost, risk, and schedule management could indirectly influence quality management by improving overall project control and precision, which are essential for maintaining quality standards. Showing a gap in studying how to integrate AI into CQM
C04	Investigating AI Applications in Construction Industry: A Systematic Review	Seyman-Güray, T	2023	This study examined AI's contributions to handling challenges in the construction industry, such as cost overruns, delay, risk, rework, and safety issues. The construction industry's characteristic resistance to new technologies is noted as it is among the least digitized sectors.	This paper provides a broad overview of AI's application in the industry. There is considerable potential for transformative impacts through AI in project monitoring, and enhanced decision-making, but does not focus deeply on quality management practices, emphasizing the gap in direct studies linking AI with CQM in construction projects.
C05	Mapping Two Decades of AI in Construction Research: A Scientometric Analysis from the Sustainability and Construction Phases Lenses	Regina et al.	2023	The paper investigated the effect of AI technology on improving sustainability, productivity, and efficiency. AI technologies such as machine learning, deep learning, and big data can affect construction projects' performance and digitize and modernize the construction industry, consolidating its processes and practices toward a more sustainable future.	The study suggests a growing trend towards integrating AI more comprehensively across all construction phases and deeper into sustainability practices. It provides broad understanding of how AI is applied in the industry but does not focus on quality management, and encourages ongoing innovation and research to overcome existing barriers to AI adoption in construction

No	Title	Author	Year	Literature Summary	Researcher Comments and relevance to JSWP
C06	A Comprehensive Literature Review of Research Trends of Applying AI to Construction Project Management	Merdžanović et al.	2023	This research investigated how AI affects construction project management, including planning, scheduling, monitoring, execution, and controlling. It emphasizes how AI can automate routine tasks, improve decision-making through data analytics, and optimize project outcomes by enhancing efficiency and accuracy.	This paper provides a foundational understanding of AI's impact on construction project management but does not delve deeply into quality management practices. While it covers AI's role in enhancing project efficiency and decision-making, the direct effects on quality management are not specifically addressed, which presents a gap.
C07	Adoption of Artificial Intelligence for Optimum Productivity in the Construction Industry	Victor	2022	This study focused on bridging the gap between AI and its advantages in the construction industry by reviewing several case studies. It also explores how AI and people should interact and the degree of human trust in AI technology.	The paper emphasizes AI's role in automating processes, improving efficiency, and aligning with lean principles, which prioritize reducing waste and increasing value. A significant part of the study discusses the level of trust between humans and AI systems as a critical factor for successful AI integration.
C08	An investigation into the Impact of Artificial Intelligence on the Future of Project Management	Alshaikhi & Khayyat	2021	This paper discussed the effect of using AI in PM; it highlights several AI tools and applications that could support project managers by automating tasks and providing analytical insights, thus improving the overall management of projects. However, it was found that AI can automate tasks but cannot replace human minutes or decrease the need for human resources.	The paper provides insights into how AI could be leveraged to automate and optimize project management tasks, which could extend to quality management practices in construction. The paper acknowledges several challenges in implementing AI in project management that require attention in future research, such as data availability, integration difficulties, high costs, and the potential impact on employment due to automation.
C09	Roles of artificial intelligence in construction engineering and management: A critical review and future trends. Automation in Construction	Pan & Zhang	2021	The study notes a shift in focus from traditional expert systems to more advanced technologies like BIM, smart robotics, cloud VR/AR, IoT, digital twins, 4D printing, and blockchain technologies. The study found AI can benefit the construction industry in terms of automation, risk mitigation, high efficiency, digitalization, and computer vision. Challenges in adoption include data quality issues, integration complexities, and investment in new technologies.	This paper directly addresses the broad applications of AI in construction but does not focus specifically on quality management. It explored AI-powered technologies to automate inspections and improve decision-making in quality control workflows. It can provides a solid foundation for understanding how AI technologies are currently used and how they can potentially transform the industry. This research will focus specifically on how AI can improve quality management practices within construction projects
C10	Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges	Abioye et al.	2021	The study explored AI applications in CE, identifying opportunities and challenges for adoption. It explored the benefits of using several AI technologies, such as CV, robotics, NLP, ML, etc. The paper offers a critical review of existing AI applications across various construction activities, highlighting how AI is being used to tackle complex problems & enhance efficiency in construction management.	AI technology uses predictive analytics, such as forecasting project delays or optimizing resource allocation and automated construction processes, enhancing precision and safety on sites. it outlines the potential and challenges of AI in construction, which can be directly relevant to this research focus on enhancing quality management through AI. However, the paper does not explore the impact on quality management practices.

No	Title	Author	Year	Literature Summary	Researcher Comments and relevance to JSWP
C11	Impact of Artificial Intelligence on the South African Construction Project Management Industry (Case Study)	Makaula et al.	2021	In this practical study the author develops a framework for applying AI in construction management across the project lifecycle. It highlights how AI can support planning, design, execution, and material sourcing while addressing labor productivity and risk management. It also identifies potential barriers, such as high costs and job security concerns.	The paper offers insights into AI's practical applications and barriers in construction, providing a comparative foundation for exploring AI integration within JSWP. Highlights specific lifecycle areas that could benefit from AI adoption which aligns with the focus of the research Juran quality tribology. However, it doesn't specifically focus on quality management practices, which provides an opportunity for this research to delve deeper into this aspect, particularly how AI can be integrated to enhance quality management in construction projects.
C12	Artificial Intelligence for Product Quality Inspection toward Smart Industries: Quality Control of Vehicle Non-Conformities	Chouchene et al.	2020	This work proposes an automated artificial vision system leveraging AI to detect vehicle defects, aligning with the principles of Industry 4.0. Additionally, a brief review of AI-based quality control methods highlights the challenges of Visual Inspection (VI) and demonstrates AI's effectiveness, particularly in vehicle manufacturing industries.	In this paper the author proposed an Intelligent Quality Management Information System (IQMIS) for real-time monitoring and optimization of quality processes in the car manufacturing industry. This approach can be insightful for developing a framework of AI-driven CQM practices for JSWP.
C13	The Effect of Using Artificial Intelligence on the Quality of Decision-Making in Various Organizations: A Critical Survey Study	El-Emary et al.	2020	The study aimed to investigate the impact of AI on the quality of decision-making in various types of organizations. The results showed a positive impact despite the organization's structure. It also discussed popular techniques and algorithms of artificial intelligence.	The paper provides a critical analysis of existing research, highlighting the use of various AI techniques like Neural Networks, Support Vector Machines, and Bayesian Networks to enhance decision-making accuracy and efficiency. Such an approach can be used in assessing and analyzing the data for the case study.
C14	Research on the Application of Intelligent Construction Site in Construction Site Management	Zhang, M	2020	This paper investigated the use of intelligent construction sites (information tech) to manage construction sites more efficiently, focusing on quality and safety problems by integrating information technologies like BIM, IoT, and cloud computing in construction management.	The paper provides evidence of how AI and related technologies can be utilized to minimize quality and safety issues, and the use of BIM technology to predict potential problems and improve communication among construction site personnel. However, the paper didn't link the positive impact of AI on safety and quality on project outcomes.

CHAPTER TWO

REVIEW OF LITERATURE

2.1 Overview

Construction Quality Management has emerged as a vital and indispensable factor in determining the success and overall performance of construction projects. CQM is a critical component that significantly contributes to achieving project goals, meeting clients' requirements, and satisfying their expectations. It encompasses a range of processes and procedures that ensure construction projects are delivered to the specified standards and quality levels, ultimately leading to enhanced customer satisfaction and the organization's ability to differentiate itself from competitors in the highly competitive construction industry. As Zhang et al. (2014) explained, organizations are often driven to implement quality management systems either by rational motivation, seeking to improve internal performance and project outcomes, or by a social motivation, aiming to conform to external expectations and gain legitimacy. Understanding these underlying drivers is essential for evaluating the effectiveness of CQM practices in achieving tangible project success.

Mega construction projects, including infrastructures, have widely acknowledged CQM as a crucial factor in enhancing project outcomes. However, the successful implementation of quality management in construction projects is not without its challenges. Understanding the relationship between Construction Quality Management and various project outcomes is crucial (Bittharia, 2021). While construction quality management practices such as quality assurance and control have been shown to significantly contribute to project success, their application can also present unique challenges that require careful navigation, especially in the absence of proper quality planning. This chapter will explore the complexities of effectively applying quality management principles within the construction industry and examine how these practices can influence key project performance metrics, including budget, schedule, quality, and customer satisfaction (Teshome & Gobana, 2018).

Understanding the challenges of implementing CQM practices in construction and infrastructure projects, and how these practices impact project outcomes, lays the foundation for incorporating emerging technologies like artificial intelligence to optimize and enhance quality management effectiveness in the construction industry (Hamdan, 2024). AI tools and techniques, such as automating quality processes, identifying and predicting quality issues, can help address the complexities of implementing effective CQM practices. AI-driven solutions can automate and streamline quality control, enable real-time monitoring and data analysis, and provide predictive insights to proactively mitigate quality-related issues. By leveraging AI, construction firms can improve the efficiency and effectiveness of their quality management practices, leading to better project outcomes in terms of cost, schedule, quality, and customer satisfaction (Regona et al., 2023).

The recent advancements in AI and digital technologies have already started to transform CQM practices. According to Luo et al. (2022) these emerging technologies can improve defect detection, compliance monitoring, and quality control efficiency. In their study, AI-driven solutions such as Building Information Modeling (BIM), Augmented Reality (AR), Internet of Things (IoT) and Computer Vision (CV) have been integrated into the quality management framework. The results were enhanced pre-construction defect prevention, reducing rework and ensuring adherence to quality standards. By leveraging AI in CQM, projects can minimize human errors, accelerate quality inspections, and enhance customer satisfaction, making it a critical tool that can leverage large-scale infrastructure projects to tackle the challenges associated with the complexities of these projects, where traditional CQM practices cannot fully address.

2.2 Theoretical Foundations of Construction Quality Management

It is crucial to understand the theoretical foundations and principles of construction quality for developing a comprehensive approach to quality management in construction. CQM is rooted in the theoretical principles and frameworks established by quality management pioneers such as W. Edwards Deming, Joseph Juran, Crosby, and Armand Feigenbaum. Deming's philosophy emphasizes process control, statistical quality management, and the Plan-Do-Check-Act (PDCA) cycle, which has become a fundamental aspect of international quality standards like ISO 9001 (Neyestani, 2016).

Juran's Quality Trilogy, quality planning, control, and improvement, has been instrumental in structuring quality processes in construction projects, ensuring that project outcomes align with client expectations and regulatory standards (Juran & Joseph, 2012). Meanwhile, Crosby's "Zero Defects" concept underscores the importance of a defect-prevention mindset, reducing rework and improving cost efficiency in large-scale projects (Crosby, 1980). These foundational concepts provide a strong theoretical basis for understanding the key elements and best practices of quality management, which have been adapted and applied to the unique context of the construction industry.

The research conducted by Neyestani, B. (2016) highlighted the effectiveness of QMS, particularly ISO 9001, in enhancing project performance across the construction industry. The study conducted in Metro Manila found that implementing robust QMS, that is adhering to strong theoretical background such as ISO 9001, had the most significant impact on customer satisfaction, followed by cost and time efficiency, with low impact on project scope. The result of this study aligns with the importance of the foundational theories of CQM, where there is a need for strong proactive planning, continuous improvement, and systematic quality control contribute to better project outcomes, especially in large scale projects.

Building on Neyestani's findings, recent empirical studies conducted in Saudi Arabia further reinforce the critical role of QMS in the construction sector. For example, Aichouni et al. (2014) examined the readiness and implementation of QMS among contractors in the Hail region and found that while awareness of ISO 9001 and TQM existed, the actual application of quality tools and practices was limited. The study highlighted that only 44% of surveyed companies had a formal ISO 9001 system, and less than half employed a quality manager, indicating a fragmented quality culture. Similarly, Abdul Hakim and Mat Naim (2006) emphasized that although many construction organizations pursue ISO 9000 certification, misunderstanding of Project Quality Plans (PQP) and a compliance-focused mindset often undermine the full realization of customer satisfaction and project performance. These findings suggest that despite the global recognition of ISO-based QMS frameworks, effective implementation in the Saudi construction context requires stronger organizational commitment, better training, and integrated project-level quality planning.

Recognizing the inherent complexities and challenges faced by construction projects, the integration of well-established quality management theories, such as those of Deming, Juran, and Crosby, provide a solid framework for effectively implementing CQM practices and addressing the specific quality-related issues that arise in the construction domain. As evidenced by empirical studies within the Saudi construction industry, however, the successful application of these principles requires not only technical knowledge but also organizational commitment, capacity building, and context-sensitive adaptation. Grounding CQM in well-established quality management theories, construction firms can develop more robust and systematic approach to enhance quality performance, reduce rework, consistently meet client & stakeholder expectations, thereby ensuring the successful delivery of construction projects that meet or exceed the specified standards, requirements, and customer expectations.

2.3 Quality Management Frameworks

2.3.1 The ISO 9000 series

The ISO 9000 series is a set of internationally recognized standards developed by the International Organization for Standardization (ISO) to establish QMS across industries, including construction. The most widely implemented standard in this series is ISO 9001, which provides a framework for organizations to ensure consistent quality, process efficiency, and customer satisfaction. These standards emphasize a process-driven approach to quality management, focusing on continuous improvement, risk-based thinking, and compliance with regulatory requirements. In construction projects, ISO 9001 certification is often required by clients and regulatory bodies to demonstrate an organization's commitment to quality assurance and compliance with industry best practices (Neyestani, 2016). ISO 9001 (2015) standard outlines seven key quality management principles that are critical in the construction industry:

1. Customer Focus: Meeting & exceeding client expectations in project execution.
2. Leadership: Ensuring quality objectives align with the organization's vision.
3. Engagement of People: Empowering employees at all levels to contribute towards quality implementation.
4. Process Approach: Managing construction activities through well-defined processes and procedures.

5. Continuous Improvement: Continually enhancing construction practices and methodologies.
6. Evidence-Based Decision Making: Using data and audits to drive quality improvements.
7. Relationship Management: Strengthening collaboration with suppliers, subcontractors, and stakeholders.

Implementing ISO 9001 in construction projects requires several important steps, including establishing a documented quality management system, conducting internal and external audits, implementing corrective actions, and continuously monitoring performance metrics. Many construction firms adopt ISO 9001-certified quality systems to streamline document control, material inspections, and compliance procedures, thereby reducing rework costs, project delays, and contract disputes. For large-scale infrastructure projects, such as stormwater networks or highway construction, ISO 9001 provides a standardized framework for managing quality across multiple contractors, subcontractors, and suppliers, ensuring consistency and reliability.

A case study conducted by Hamdan, M. (2024) on the construction of a 22-kilometer stormwater network in the UAE highlights the importance of strict quality assurance procedures in achieving project success. The study found that rigorous material testing, site inspections, and adherence to documented quality protocols were essential in preventing defects and ensuring compliance with client expectations.

Supported by another by Khalfan et al. (2020) while investigating ISO 9001 certified construction industry and found that TQM practices, such as leadership involvement, employee training, supplier integration, and process control, serve as key drivers of operational performance. Their research underlined that projects with a strong quality culture and continuous improvement mechanisms are more likely to experience smooth transitions from execution to maintenance, minimizing rework and cost overruns. Together, these findings underscore how structured quality management systems, grounded in TQM principles, enhance the durability and efficiency of large-scale infrastructure projects.

Another study on Malaysian construction projects conducted by Mukhtar et. al. (2010) revealed that ISO 9001-certified contractors experienced fewer non-conformance reports (NCRs), lower material wastage, and reduced rework costs, leading to better project performance and financial savings. The research emphasized that one of the core aspects of ISO 9001 is its focus on performance measurement and continuous improvement, which is particularly relevant for large-scale infrastructure projects. The quality cost approach, which includes prevention, appraisal, and failure costs, was identified as a crucial tool for assessing and improving construction quality performance. However, the study also noted that knowledge gaps among project teams often limit the full potential of ISO 9001, highlighting the need for better training and awareness programs to enhance its effectiveness.

Implementing ISO 9001 Quality Management and ISO 14001 Environmental Management have significantly contributed to the operational success of DB Construction, leading to a 34% annual growth. According to BSI (2011), the integration of these management systems helped the company enhance process efficiency, improve client satisfaction, and strengthen compliance with regulatory requirements. Adopting structured quality management practices by DB Construction helped the company to reduce inefficiencies, streamline documentation, and improve overall project performance, demonstrating the value of internationally recognized quality standards in the construction industry.

These examples reinforce how ISO 9001-based QMS frameworks enhance efficiency, reduce costly rework, improve stakeholders' satisfaction and contribute to the overall durability of infrastructure projects. In large-scale infrastructure projects like JSWP, ISO 9001 is critical, as it involves multiple stakeholders, complex materials supply chains, and stringent regulations and client needs, requiring a structured quality management system to ensure compliance, minimize defects, and improve efficiency. Contractors are required to fully adopt ISO 9001 and align their QMS with JSWP's standards, as it plays a vital role in ensuring quality consistency and enhancing project efficiency. Integrating JSWP's quality requirements into a comprehensive Quality Manul, contractors can standardize their Inspection and Test Plans and Method Statements, fostering proactive defect prevention, better stakeholder coordination, and smoother project execution.

However, contractors often implement QMS either to align with strategic project goals or to meet regulatory, industry, or project requirements. Zhang et al. (2014) distinguished between the rational perspective, where quality systems are strategically adopted to improve performance, and the social perspective, where they view ISO 9001 as a bureaucratic formality, focusing on passing audits rather than improving quality on-site, which is the case for some contractors in JSWP. In such cases, Quality Manuals are generic, developed only for certification or approval purposes, leading to inconsistent quality control, task delays, and frequent revisions.

Another study from Jordan's construction industry revealed that many ISO-certified firms had employees unaware of the standard's actual significance, reflecting poor implementation and weak integration into daily activities. This reactive approach results in higher defect rates, increased rework costs, and misalignment with quality objectives, ultimately delaying project progress and increasing contractual disputes (Hiyassat, 2000). Such disparities in ISO 9001 adoption are evident within JSWP, which highlights that the true value of a QMS lies in its meaningful implementation, not just its certification.

2.3.2 Total Quality Management (TQM)

TQM is a comprehensive quality approach that focuses on continuous improvement, customer satisfaction, and proactive defect prevention throughout a project's lifecycle. In the construction industry, TQM principles help ensure that quality is embedded at every stage, from planning, design to execution and project handover. Which is not like the traditional quality control methods, that focus on defect detection after occurrence. TQM emphasizes preventive strategies, such as process optimization, employee engagement, and data-driven decision-making.

Several major construction firms have successfully implemented TQM to enhance project outcomes. For example, Bechtel Corporation, a globally recognized engineering and construction company, adopted TQM methodologies and Six Sigma principles to improve processes, reduce construction defects, and minimize the cost of defects and rework. By integrating structured quality control procedures into daily site operations, Bechtel's quality improvement initiatives resulted in \$200 million in savings, following an initial investment of \$30 million in a defect prevention and process optimization

program (Oguz et al., 2012). This case highlights how TQM-driven quality management strategies can lead to significant cost reductions and improved project efficiency in large-scale construction projects.

In Saudi Arabia, the implementation of TQM is increasingly recognized as a key strategy for enhancing project performance and competitiveness in the construction sector. While global frameworks such as ISO 9001 have provided structured foundations for quality systems, their real impact lies in how effectively TQM principles are embedded within project execution. A study by Mazher, Gharleghi, and Fah (2015) investigated four key TQM dimensions, quality management, quality control, quality assurance, and quality inspection, within Saudi construction firms, finding that the first three had a statistically significant positive impact on project quality. Notably, quality management showed the strongest correlation, emphasizing the importance of strategic planning, leadership commitment, and systematic process management. These findings complement those of other studies in the region, which suggest that employee engagement, continuous improvement, and integrated quality frameworks are essential to achieving project success.

For large-scale infrastructure programs like JSWP, these insights affirm that TQM and ISO 9001 must go beyond documentation and compliance to become a fully embedded organizational culture, throughout the project's lifecycles, enabling better coordination, reduced defects, and enhanced client satisfaction. The implementation of TQM in large-scale infrastructure projects in Saudi Arabia, such as the Riyadh Metro, has faced challenges. While TQM provided strict quality planning, assurance, and continuous monitoring that can minimize construction errors in some cases, there have also been reports of quality-related issues and major delays. Contractors may have struggled to fully integrate TQM principles into their daily operations, leading to inconsistent quality control and a disconnect between the intended benefits and the actual project outcomes (Abazid, 2017).

While TQM is widely recognized for its benefits in construction, it is not formally implemented in JSWP, as ISO 9001 is followed as its quality management framework. However, the core principles of TQM, continuous improvement, defect prevention, and process optimization, are inherently embedded within ISO 9001 requirements.

Contractors working under JSWP are expected to apply ISO 9001-driven quality management processes, such as structured ITP, MOS, and Material Inspection Requests to maintain compliance and ensure consistency across all projects. The effectiveness of ISO 9001 still depends on how well contractors integrate quality practices into their daily operations rather than treating compliance as a procedural obligation.

To summarize, the construction industry's adoption of structured quality management systems, such as ISO 9001 and TQM, has demonstrated significant benefits in enhancing project outcomes, reducing defects, and improving overall efficiency. These frameworks provide a systematic approach to managing quality across the project lifecycle and have been widely embraced in both global and regional contexts. Within the Jeddah Stormwater Program, ISO 9001 serves as the primary quality framework, offering a standardized structure for quality manuals, ITPs, and MOS, but the meaningful implementation of its principles is crucial for realizing its full potential in improving construction quality, cost, and performance.

2.4 The Quality Gurus

2.4.1 Juran's Quality Trilogy in Construction

Juran's Quality Trilogy, developed by the pioneer quality management expert Dr. Joseph Juran, is a foundational framework in the field of quality management. This model consists of three interrelated processes: Quality Planning, Quality Control, and Quality Improvement. It emphasizes a proactive approach to quality management, ensuring that defects and inefficiencies are minimized through structured planning, continuous monitoring, and data-driven improvement (Juran & Joseph, 2012).

Although Juran's Quality Trilogy traditionally consists of three quality processes, this study operationalizes the trilogy into four CQM dimensions to better reflect the practical structure of quality management in construction projects. Quality Assurance and Quality Control are commonly treated as distinct complementary functions. Quality Assurance focuses on system-level prevention, audits, procedures, management reviews, compliance governance, and process effectiveness. In large infrastructure programs, such as JSWP, this function is usually led at PMO/PMCM or program governance level to ensure that quality systems, procedures, and compliance requirements are consistently applied across projects.

By contrast, Quality Control focuses on inspecting, testing, defect identification, NCRs, SORs, and field verification, which are usually performed or verified at the site level by the supervision consultant and contractor teams. Therefore, the control logic within Juran's Trilogy is operationally expanded in this study by distinguishing Quality Assurance and Quality Control as separate measurable dimensions. This adoption does not replace Juran's theory; rather it extends its applicability to the construction project environment, where assurance and control activities are institutionally and operationally separated.

In construction projects, Juran's principles remain useful for improving project execution, reducing waste, minimizing rework, and supporting cost efficiency and infrastructure reliability. However, the dynamic and complex nature of construction projects means that the traditional trilogy may require contextual adaptation. A one-size-fits-all application may not fully accommodate project-specific constraints, multiple stakeholders, changing site conditions, and fragmented responsibilities. In such context, excessive documentation and formal procedures may also become bureaucratic if they are applied only for compliance rather than as part of an active quality governance system.

In the context of construction projects, Juran's Quality Trilogy can serve as a comprehensive quality management strategy. Juran's principles are widely applied to enhance project execution, cost efficiency, and long-term infrastructure reliability. By integrating these three quality management processes, construction firms can systematically plan for quality, actively control and monitor quality-related activities, and continuously improve their quality management practices. This comprehensive approach helps construction organizations achieve their desired project outcomes, meet or exceed customer expectations, and deliver high-quality infrastructure that stands the test of time.

Although JSWP primarily adopts the ISO 9001 quality management framework as a contractual quality management framework, the core element of Juran's Quality Trilogy is aligned with the structured approach of ISO 9001. Contractors working under JSWP are required to apply quality planning through project quality plans and quality manuals; quality control via Inspection and Test Plans and rigorous inspections, quality

assurance and improvement through continuous audits, corrective actions and preventive actions, lessons learned, and continuous process improvement. Effective integration of these complementary principles through ISO 9001, JSWP contractors can foster a proactive quality management mindset, and rather than merely reactive compliance when ISO is only a formality that needs to be done. This approach can help reduce defects, optimize processes, and ultimately improve overall project outcomes.

2.4.2 Deming's PDCA Cycle in Construction

Deming's Plan-Do-Check-Act (PDCA) Cycle is a widely used continuous improvement model that emphasizes an iterative approach to quality management. Initially developed by Dr. W. Edwards Deming, the PDCA cycle ensures that quality is managed proactively rather than reactively, making it particularly valuable in construction projects where deviations from standards can lead to significant cost overruns, delays, safety risks, and reduced customer satisfaction. The cycle consists of four key stages as shown in Figure (02) below.

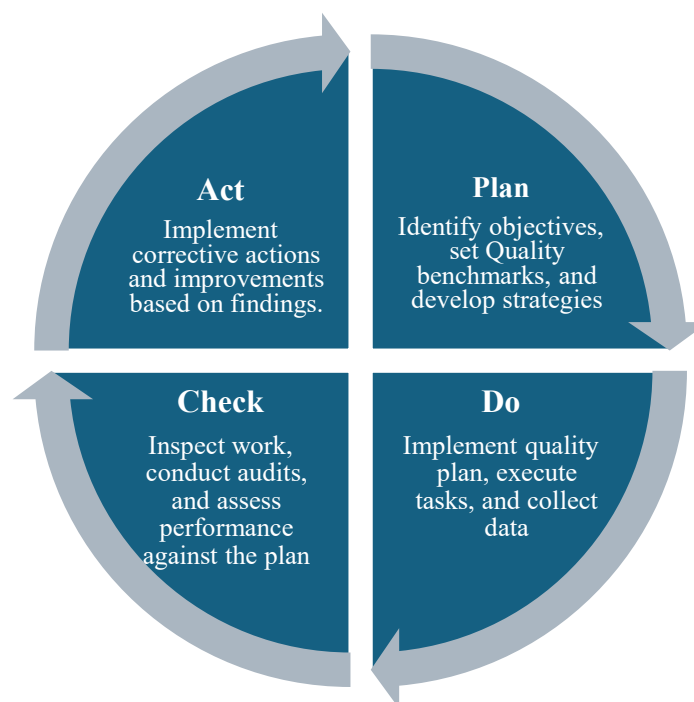


Figure 02: Deming Cycle PDCA
Source: Adapted form Deming (1986)

In Construction, the PDCA cycle is widely applied in construction to ensure proactive quality management, prevent defects, and drive continuous improvement. In the Cross-rail Project (London's Elizabeth Line), the Plan phase was used extensively to define quality benchmarks, conduct risk assessments, and develop quality control strategies, preventing material failures and structural weaknesses before construction began (Project and Program Management, 2023). Check phase played a crucial role in the Hong Kong-Zhuhai-Macao Bridge project, where frequent inspections and real-time monitoring were used to detect early signs of structural stress and ensure compliance with engineering standards, reducing post-construction defects (Zhu et al., 2018). The act phase was used in the Riyadh Metro project, where lessons of early phases led to better material selection, workflow efficiency, and safety improvements, minimizing rework and enhancing overall project quality (Abazid, 2017). These examples demonstrate how the PDCA cycle systematically integrates planning, monitoring, and corrective actions to improve project outcomes, reduce defects, and optimize construction processes.

The author considers the PDCA cycle as an important model in large infrastructure projects as it creates a continuous feedback loop that enables consultants and contractors to identify and address quality issues at every stage of the project lifecycle. Within the Jeddah Stormwater Program, the application of Deming's PDCA cycle is evident in the structured quality management system required by the ISO 9001 framework, this model can help in integrating lessons learned from finished projects into new projects, especially during the planning stage, to incorporate lessons learned into the packages before reaching the bidding stage.

2.4.3 Crosby's "Zero Defects" Philosophy in Construction

Philip Crosby's "Zero Defects" philosophy is a quality management approach that emphasizes doing things right the first time (DRIFT) to eliminate defects, reduce rework, and enhance project efficiency. Unlike traditional quality models that focus on detecting and correcting errors after they occur, Crosby's methodology promotes a preventive mindset, as quality is built into processes rather than inspected at execution stage (Crosby, 1980). This principle is relevant in large-scale construction projects, where issues in materials, workmanship, or execution can lead to significant cost overruns, delays, and safety issues.

2.4.4 From Traditional Quality Management to Quality 4.0

While traditional quality management theories such as Juran's Trilogy, Deming's continuous improvement philosophy, ISO 9001, and TQM provide the theoretical foundation for understanding CQM, the increasing complexity of modern infrastructure projects requires a more digitally enabled perspective. Quality 4.0 represents this contemporary extension by integrating traditional quality principles with digital technologies such as Artificial Intelligence, big data analytics, automation, digital dashboards, Building Information Modeling, Internet of Things, and predictive monitoring systems.

In the context of construction projects, Quality 4.0 does not replace traditional quality management theories. Rather, it strengthens their practical application by improving data visibility, accelerating issue detection, supporting predictive decision making, and enabling more integrated quality governance. For example, quality planning can be enhanced through historical data analysis, quality assurance can be supported by digital audits and automated compliance monitoring, quality control can be improved through real-time inspection data and defect trend analysis, and quality improvement can be strengthened through AI-supported root-cause analysis and lessons-learned systems.

This perspective is particularly relevant to the present study because the research examines the role of AI in the relationship between CQM and project outcomes. The findings showed that AI has a significant direct effect on project outcomes, but its moderating role was not statistically supported. From a quality 4.0 perspective, these results suggest that AI is currently functioning as an operational enhancer rather than as a fully integrated quality governance mechanism. Therefore, the transition from traditional CQM to AI-enhanced CQM requires not only the adoption of AI tools, but also stronger data governance, integrated digital platforms, organizational readiness, and executive-level digital quality governance.

Accordingly, Quality 4.0 provides a contemporary theoretical lens that links the traditional quality theories used in this study with the emerging role of AI in construction quality management. It supports the study's argument that effective AI integration depends on the maturity of existing quality systems, the availability of reliable project data, and the degree of digital integration across project stakeholders.

2.4.5 Application in Construction

Crosby's "Zero Defects" philosophy has been successfully applied in various high-profile infrastructure projects, presenting its effectiveness in enhancing quality control and reducing rework. The implementation of strict quality planning, supplier compliance audits, and defect-prevention strategies has helped minimize construction errors and material defects, ensuring that the work meets stringent regulatory and safety standards (Salvi & Kerkar, 2020). This approach, which focuses on doing things right the first time, has been instrumental in improving the long-term performance of construction projects by eliminating material inconsistencies and structural defects.

While the ISO 9001 framework is the primary quality management system in JSWP, Crosby's principles are already embedded in the program's quality approach. Contractors are required to establish comprehensive Quality Manuals, ITPs, and MOSs to ensure quality is controlled at every stage of construction. The contractors who adhere to JSWP's quality standards, implement supplier audits, inspections, and defect-prevention strategies, are aligning with Crosby's "Zero Defects" philosophy. However, when no planning is in place, Crosby's zero-defect approach may not be effective, which highlights the importance of integrating both the PDCA cycle and Crosby's principles into the quality management system to drive continuous improvement and eliminate defects throughout the construction lifecycle (Hwang & Yang, 2014) (Alinizzi et al., 2020).

2.4.6 Conclusion and Proposed Solution

Construction Quality Management is a crucial aspect of large infrastructure projects, as it directly impacts project outcomes in terms of cost, schedule, quality, and customer satisfaction. The PDCA cycle and Crosby's "Zero Defects" philosophy provide effective frameworks for implementing a proactive and preventive quality management approach in the construction projects. Integrating these principles into the construction process can help construction project teams to identify and address quality issues, minimize defects. This will drive continuous improvement and enhance the overall performance leading to success of the project.

Therefore, the theoretical framework of this study combines traditional quality management theories with the contemporary perspective of Quality 4.0, which adopts digital technologies and data driven systems to enhance quality governance, predictive control, real-time monitoring, and continuous improvement. This combination provides a suitable foundation for the study, by examining how CQM practices affect project outcomes and how AI may enhance, support, or eventually moderate this relationship in digitally mature construction environments.

In this study, Quality 4.0 acts as the contemporary theoretical bridge between traditional quality management principles and AI-enabled CQM. Traditional theories explain the foundation of planning, assurance, control and improvement, while Quality 4.0 explains how these foundations can be strengthened through digital technologies, data integration, predictive analytics, automation, and intelligent decision support. Accordingly, the research model is not based solely on classical quality theories, but on their extension into digitally enabled construction environment where AI can support, enhance and potentially moderate the relationship between CQM practices and project outcomes when sufficient digital maturity exists.

2.5 The Pyramid of Quality

The author developed the pyramid of quality integration to illustrate the evolution of quality thought and its structured application within the construction industry. Figure (03) illustrates the layered integration of quality management thinking into construction practices, showing how foundational theories have evolved into structured systems that drive modern project outcomes. At its foundation are the contributions of quality pioneers, Deming, Juran, and Crosby, who introduced key principles such as continuous improvement, process focus, and defect prevention. These theoretical contributions informed the rise of TQM in the 1980s, emphasizing organizational culture, leadership, and system-wide quality responsibility. Subsequently, the development of the ISO 9001 standard translated these principles into a formalized quality management framework, emphasizing process control, documentation, and continuous auditing.

Within the construction sector, these standards were further operationalized through Construction Quality Management (CQM) practices, including Quality Management Systems, Inspection and Test Plans, Non-Conformance, and on-site inspections. At the

top of the pyramid lie the intended results of these layered practices: project outcomes in terms of cost, time, quality, and customer satisfaction.

As construction projects become larger, more complex, and increasingly data-driven, the traditional quality pyramid requires a contemporary extension through Quality 4.0. In this study, Quality 4.0 is not treated as replacement for the traditional quality theories, but as a digital layer that enhances its practical application through emerging technologies. This provides the basis for the later AI-enhanced Pyramid of Quality, where digital intelligence is positioned as an enabler of stronger quality planning, assurance, control, and improvement.

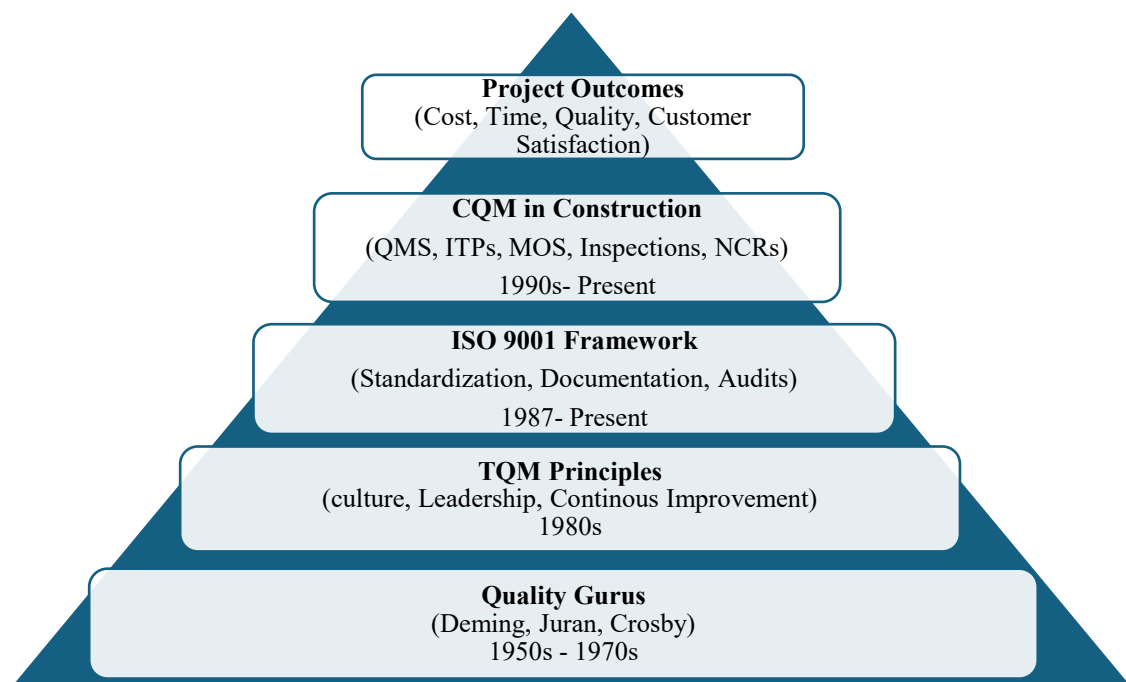


Figure 03: Pyramid of Quality Integration into Construction
Source: Developed by the Author

2.5.1 How ISO 9001 Acts as Integrative Framework

Elements of the discussed quality management theories and models are inherently implemented within JSWP as the program officially adheres to ISO 9001 as its primary quality management system, its implementation naturally integrates fundamental principles from the quality theories. Figure (04) illustrates how the foundational principles and concepts introduced by quality pioneers shaped the development of structured frameworks like TQM and ISO 9001, forming the theoretical backbone of modern quality systems.

From Deming, ISO 9001 inherits the PDCA cycle, process orientation, and emphasis on continuous improvement. While Juran quality trilogy incorporates a structured approach to quality planning, control and improvements, Crosby, reflects the preventive approach over proactive inspections. ISO formalizes TQM's broader concepts of customer satisfaction, employee & management involvement, and system-wide quality responsibility into documented procedures, measurable objectives, and audit processes.

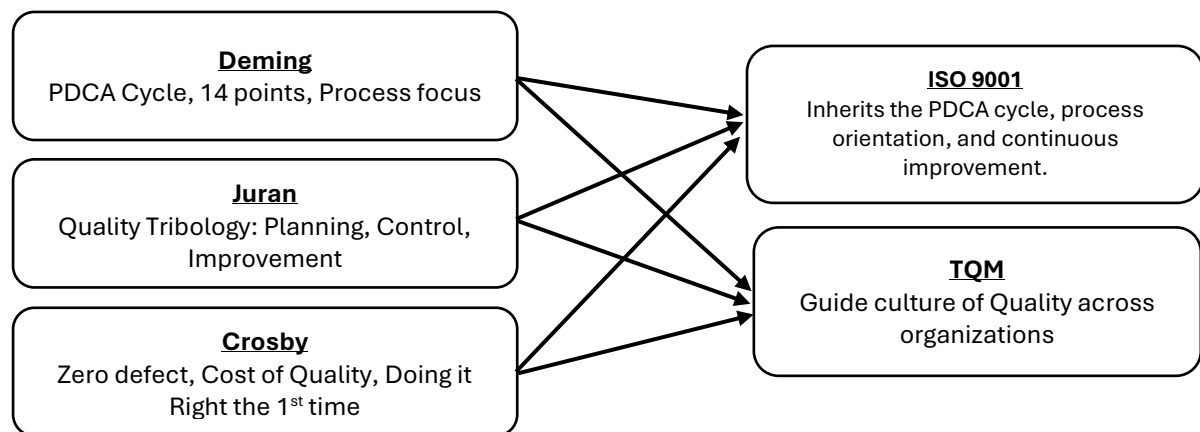


Figure 04: Contributions Of Quality Gurus to Modern Management Frameworks
Source: Developed by the Author

Building on the previous discussion of Figure (04), the overlapping principles of Deming, Juran, and Crosby highlight a shared foundation that underpins modern quality management systems. The Venn diagram on Figure (05) below shows how Both Deming and Juran advocate for continuous improvement, while Crosby and Deming stress defect prevention over post-inspection correction. Juran and Crosby align on the need for structured planning and clear accountability in quality implementation. These overlapping principles not only reinforce the theoretical consistency behind modern frameworks like ISO 9001 and TQM but also justify their integration into Construction Quality Management (CQM) systems used in complex infrastructure projects such as the Jeddah Stormwater Program (JSWP). The interaction of All three emphasizes customer satisfaction, measurable performance, and organizational commitment to quality which are the core values of modern quality management frameworks.

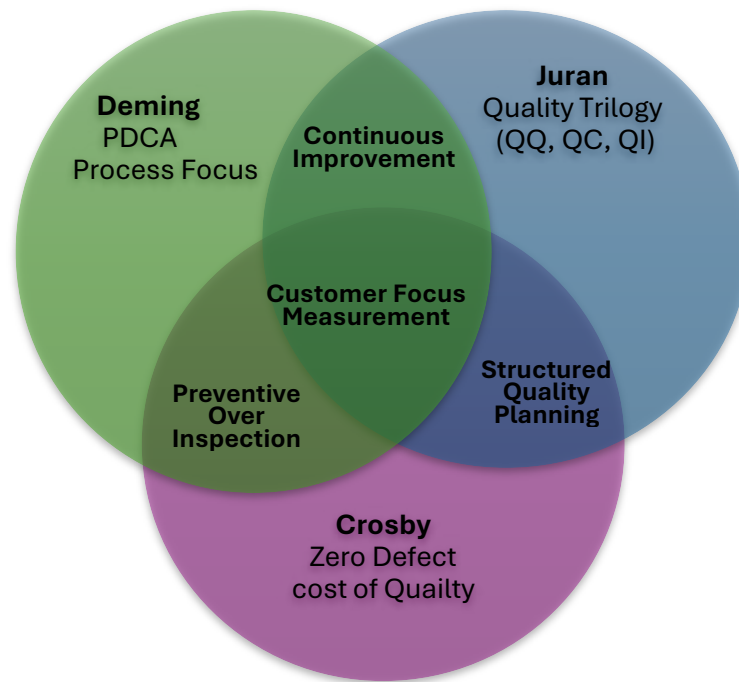


Figure 05: Overlapping Principles of Deming, Juran and Crosby
Source: Developed by the Author

2.5.2 Proposed Solution

The success of JSWP's quality efforts ultimately depends on how contractors and stakeholders apply these principles in practice through a combined framework. Therefore, quality management in JSWP is not defined by a single theory but rather by a hybrid approach that combines the best practices from various models, tailored to the program's specific needs and challenges. In this sense, ISO 9001 functions as a key player that bridges theory and practice, offering a structured pathway for implementing CQM across diverse construction environments, including complex multi-stakeholder programs like JSWP.

With the increased size and complexity of projects challenges persist. The lack of top management commitment, inadequate training, and the implementation of ISO 9001 requirements as a bureaucratic obligation often results in a weak and inconsistent implementation of the quality management system. To address these challenges, construction companies involved in JSWP, and similar large-scale infrastructure programs should prioritize executive-level engagement in quality planning and monitoring. At the operational or execution level, quality initiatives for site engineers, supervisors, and quality personnel are essential to bridge the gap between policy and

execution. In addition, the integration of digital quality management tools, such as automated submittal workflows, mobile inspection platforms, and real-time dashboards, can help standardize compliance processes and improve transparency across contractors and subcontractors.

Furthermore, the adoption of AI technology in CQM presents a transformative opportunity to help overcome challenges of existing QMS, and to move from reactive to predictive quality management. AI-powered tools, including computer vision for defect detection, machine learning algorithms for quality risk prediction, and natural language processing for document review—can significantly reduce inspection time, identify patterns in non-conformances, and enhance decision-making accuracy. Embedding AI into quality workflows can help construction companies optimize inspection and testing practices and align quality performance with broader project and company objectives. These intelligent systems, when combined with human oversight and leadership commitment, offer a strong strategy for enhancing CQM practices and ensuring that quality becomes a measurable, data-informed driver of project success in JSWP and beyond.

2.6 Construction Quality Management (CQM)

Construction Quality Management is a comprehensive approach incorporating a wide range of practices and processes designed to ensure delivery of construction projects. The goal is to meet or exceed the specified standards, requirements, and customer expectations by implementing various quality control and assurance measures throughout the project lifecycle. The aim is to optimize project outcomes and enhance customer satisfaction.

Quality in construction is about adherence to appropriately established standards and specifications. It's a management approach to ensure the construction process is completed within the specified quality requirements, on time, within budget, safely, and meeting customer expectations. CQM involves systematically organizing and coordinating various processes, including planning, implementing, and monitoring quality-related activities to achieve the desired outcomes. (Teshome & Gobana, 2018).

According to the influential quality management scholars Juran and Godfrey, CQM involves the comprehensive coordination and integration of all quality assurance and quality control activities throughout the entire project lifecycle. Juran and Godfrey (Juran & Joseph, 2012) emphasize that CQM is not merely about inspections and checklists, but rather a proactive, end-to-end management system that aligns all quality-related processes and procedures to ensure the successful delivery of the construction project. Adopting this quality management approach is essential for achieving the project's objectives and meeting the specified requirements and standards.

The author highlights that effective CQM requires a strategic, systematic, and collaborative approach from all key project stakeholders, including owners, contractors, subcontractors, and designers, to work towards achieving the desired project outcomes. This comprehensive and integrated approach is crucial for ensuring that quality-related activities and processes are aligned with the overall project objectives and coordinated throughout the project lifecycle. By actively engaging all stakeholders and fostering a shared commitment to quality, CQM can optimize project performance in terms of cost, schedule, quality, and customer satisfaction. On the other hand, if construction firms do not adopt this comprehensive approach, it can lead to significant challenges and suboptimal project outcomes, as the following examples listed by Low & Ong (2014):

- Increased project costs due to the need for rework, waste, and inefficiencies
- Delays in project schedules from quality-related issues and errors
- Compromised quality of the final product or infrastructure
- Reduced project life cycle and sustainability of the project
- Dissatisfied customers and a damaged reputation for the construction firm

Therefore, the effective implementation of a robust CQM system is essential for construction firms to achieve their desired project outcomes and meet the expectations of their clients and stakeholders. To achieve that, the industry must address the key challenges associated with CQM implementation and explore innovative solutions to optimize its effectiveness, such as integrating emerging technologies and AI.

2.6.1 Construction Quality Management Dimensions

Establishing effective and fundamental principles that underpin successful construction quality management practices. Building into Juran's Trilogy Construction Quality Management will be divided into four critical dimensions that ensure project success: Quality Planning, Quality Control, Quality Assurance, and Quality Improvement. Each of these dimensions plays a vital role in maintaining compliance with standards, minimizing defects, improving efficiency, and enhancing project outcomes (cost, schedule, quality, and customer satisfaction). In large infrastructure projects, these dimensions contribute to the effectiveness of the quality management system, ensuring construction activities adhere to regulatory, contractual, and performance requirements.

2.6.1a Quality Planning

Quality Planning is the core of Construction Quality Management, it serves as a proactive strategy by defining quality objectives, standards, and procedures before construction begins. It helps in establishing all project requirements, including materials, workmanship, safety, and compliance with regulations, in advance. Effective Quality Planning helps to prevent defects, minimize rework, and align project execution with stakeholder expectations, ultimately contributing to cost efficiency, schedule adherence, and improved overall project outcomes (Juran & Joseph, 2012).

One component of Quality Planning is establishing clear quality objectives based on contract specifications, engineering standards, and regulatory codes, such as the Saudi Building Code and ISO 9001 guidelines. These objectives define the minimum acceptable standards for construction activities, to ensure that materials, processes, and workmanship meet the predefined requirements. For example, in metro rail projects, strict adherence to track alignment, concrete strength, and vibration resistance is a core quality objective to maintain long-term structural integrity.

Another component of Quality Planning is identifying potential risks and developing mitigation strategies. This includes conducting risk assessments to detect quality failures, material inconsistencies, and execution errors before they escalate. For instance, during the Palm Jumeirah project in Dubai, early identification of soil settlement risks led to the use of enhanced compaction techniques and real-time monitoring, ensuring the stability of the artificial islands (Higgins, 2013).

Another vital part of Quality Planning is developing ITPs and MOSs to ensure that construction activities are executed correctly as per requirements. These documents outline inspection frequency, acceptance criteria, and corrective measures, serving as essential tools for maintaining compliance with quality standards. A good example is the Hong Kong-Zhuhai-Macao Bridge project, where rigorous concrete durability and steel reinforcement testing protocols were implemented, preventing premature material degradation (Zhu et al., 2018). Additionally, proper documentation and compliance management are integral to Quality Planning. Maintaining traceable records of quality inspections, material certifications, and work approvals is crucial for regulatory compliance, particularly in ISO 9001-certified projects.

2.6.1b Quality Control

Quality Control (QC) in construction is the systematic process of monitoring, inspecting, and verifying construction activities to ensure compliance with project specifications, regulatory requirements, and contractual obligations. Unlike Quality Planning, which focuses on pre-construction strategies, Quality Control is done during construction to detect defects, deviations, and non-conformities in real-time. Effective QC practices minimize rework, reduce project delays, and enhance overall structural integrity, ultimately improving project outcomes in terms of cost, schedule, quality, and customer satisfaction.

A fundamental aspect of Quality Control is conducting regular inspections and material testing to verify compliance with project specifications. This includes pre-construction material testing, in-process quality checks, and final inspections before project handover. For example, in the Hong Kong-Zhuhai-Macao Bridge project, engineers implemented real-time structural health monitoring and material testing to prevent premature degradation and ensure durability (Zhu et al., 2018). On the other hand, during the construction of the Riyadh Metro, comprehensive NDT protocols were applied to detect cracks, defects, and voids in concrete and steel structures, enabling timely corrective measures (Abazid, 2017).

Another key component of Quality Control is the use of ITPs and NCRs to document inspection procedures, acceptance criteria, and corrective actions for defects. ITPs ensure that all critical construction activities, such as reinforcement, waterproofing, and

placement of concrete, undergo systematic quality verification before proceeding to the next stage. When non-conformities arise, NCRs help track deviations, analyze root causes, and implement corrective actions, ensuring that defects are addressed efficiently to prevent costly rework.

However, as highlighted in the stormwater network project case study (Hamdan, 2024), the lack of strict adherence to quality control measures such as ITPs and NCRs led to delayed defect identification and inefficient corrective actions. While QMS was in place, its inconsistent enforcement among contractors resulted in quality violations, increased rework, and project delays. The absence of proactive quality control procedures meant that defects in material storage, trench excavation, and reinforcement installation were often detected too late, causing costly rework and timeline disruptions. This case emphasizes the critical role of early intervention and strict quality monitoring in ensuring compliance with project specifications and minimizing inefficiencies (Hamdan, 2024).

Quality Control also includes the implementation of statistical process control techniques to monitor and improve the processes. Analyzing data from material testing, inspection results, and other quality metrics, can help construction firms to identify opportunities for process improvement, adjust procedures, and ensure consistent quality across multiple project sites. This process can be even enhanced using artificial intelligence technologies, which can help construction firms automate data analysis, predict quality issues, and optimize QC workflows.

In conclusion, Quality Control is an essential dimension of CQM that ensures compliance with project specifications, reduces defects, and enhances overall project reliability. In JSWP and other large-scale infrastructure projects, well-structured inspection and testing procedures, combined with effective defect management strategies, contribute to cost reduction, schedule efficiency, and long-term performance of constructed assets. However, the effectiveness of Quality Control depends on how consistently contractors implement and adhere to these processes, reinforcing the need for strict compliance with ISO 9001 and project-specific quality requirements.

2.6.1c Quality Assurance

Quality Assurance (QA) in construction is a proactive approach that focuses on preventing quality issues before they occur, in contrast to the reactive nature of Quality Control. QA is a preventive, process-oriented approach that ensures quality is built into every phase of the project lifecycle. Unlike QC, which focuses on detecting and correcting defects, QA emphasizes establishing standardized procedures, best practices, and compliance frameworks to prevent defects from occurring in the first place. QA ensures that contractors adhere to project specifications, industry regulations, and contractual requirements, ultimately improving cost efficiency, schedule adherence, and long-term durability (Juran & Joseph, 2012).

A fundamental aspect of Quality Assurance is the establishment of a Quality Management System (QMS) that provides a framework for managing quality on the project. This includes developing Quality Manuals that document quality policies, procedures, and responsibilities to ensure that all stakeholders—contractors, consultants, and suppliers—follow consistent quality standards. Another key element of QA is the implementation of regular audits, management and compliance reviews to verify adherence to established quality procedures. These audits help identify gaps in quality processes, areas for improvement, and necessary corrective actions.

Quality Assurance (QA) includes the prequalification of suppliers and subcontractors to ensure that only high-quality materials and certified vendors are used in the projects. The process includes strict supplier evaluation and approval procedures, where all materials must be procured from approved sources as per tender documents, any changes in suppliers must be closely monitored. Patel et al. (2021) found that before implementing ISO 17020, poor supplier selection and inadequate material storage led to quality inconsistencies and defects.

However, with a structured quality assurance framework, projects saw significant improvements in material handling, supplier compliance, and adherence to quality standards. This proactive approach reduces the risk of structural defects, enhances construction durability, and ensures that materials meet regulatory and project-specific requirements.

Quality Assurance is a preventive approach that establishes systematic procedures and quality frameworks to maintain high construction standards throughout a project. In JSWP, the project management office consultant (PMO) plays an important role in ensuring consistency, supplier accountability, and minimizes defects and rework. Quality Control, led by the Supervision Consultant, focuses on identifying and correcting defects, QA ensures that quality failures are avoided from the start. However, the effectiveness of QA depends on how well contractors implement and adhere to these processes, and their strict compliance with ISO 9001 standards and project-specific quality requirements.

2.6.1d Quality Improvement

Quality Improvement (QI) in construction goes beyond the traditional approaches of Quality Control and Quality Assurance. QI in construction is a continuous process of analyzing project performance, identifying areas for enhancement, and implementing corrective actions to achieve higher efficiency, reduced defects, and better overall project outcomes. Unlike QA, which establishes preventive processes, and QC, which detects and corrects defects, Quality Improvement focuses on learning from past experiences and refining construction practices over time. By systematically improving quality standards, construction firms can minimize inefficiencies, lower rework costs, and optimize long-term project sustainability.

A key component of Quality Improvement is the use of lessons learned and post-project evaluations to refine construction practices. Many successful infrastructure projects, such as the London Cross rail project, implemented structured post-construction reviews to identify quality issues, assess material durability, and optimize design practices for future phases. By analyzing previous project deficiencies, construction firms can implement corrective actions and prevent recurring defects (Project and Program Management, 2023).

Another key component of Quality Improvement is the use of data analytics and performance measurement. Construction companies can leverage data from project management systems, quality control processes, and customer feedback to identify patterns, detect root causes of quality issues, and develop improvement strategies. For

example, by analyzing inspection reports and defect logs, firms can pinpoint the most common types of quality failures, assess their impact on project outcomes, and implement corrective training, process changes, or technological solutions to address these recurrent problems (Abdullah et al., 2005).

Furthermore, Quality Improvement also emphasizes the importance of fostering a strong quality culture within construction organizations. Combined with training skill development programs, and continuous learning, this promotes a proactive mindset among project teams, empowering them to identify and address quality problems as they emerge. Well-trained workers and engineers are more likely to follow the best practices, identify quality risks early, and contribute to continuous process optimization (Naor et al., 2008).

Quality Improvement is a long-term approach that aims to refine construction processes, enhance defect prevention strategies, and adopt advanced quality techniques. In the JSWP project, this area requires major attention from all stakeholders. Lessons learned, technological advancements, and workforce training initiatives can play a crucial role in continuously improving project quality. Quality Assurance and Quality Control focus on maintaining predefined standards, Quality Improvement ensures that standards developed based on real-world project experiences. The effectiveness of Quality Improvement depends on an organization's commitment to innovation, proactive problem-solving, and adaptability to changing construction challenges.

2.7 Construction Quality Management, Project Outcomes, and AI

Quality management in construction is a critical aspect that can significantly impact project outcomes. The effectiveness of CQM is directly linked to the success of construction projects, which is commonly measured through four key project outcomes: cost, schedule, quality, and customer satisfaction. These project outcomes define the overall efficiency, performance, and success of a construction project. Also, it determines whether it meets its intended objectives and stakeholder requirements. Effective CQM practices can contribute to optimizing these key project outcomes, leading to better financial performance, timely project delivery, high-quality construction, and enhanced customer satisfaction (Neyestani, 2016).

2.7.1 Cost

The financial aspects of project execution, including budgeting, controlling and minimizing cost overruns, and optimizing the efficiency of resource utilization to ensure the project is delivered within the planned budget constraints. Effective CQM practices can contribute to cost savings by reducing waste, rework, and material defects, as well as improving productivity and resource allocation.

2.7.2 Schedule (Time)

The timely completion of construction activities according to milestones, deadlines, and schedule requirements is a critical outcome of construction quality management. It is critical to ensure that projects are delivered on time, meeting stakeholder expectations, maintaining cash flow, and avoiding penalties or reputational damage (Sota, 2017). Effective quality management practices, such as thorough planning, resource allocation, and progress monitoring, can contribute to the successful and timely delivery of construction projects

2.7.3 Quality

The degree to which the construction project meets or exceeds the specified design requirements, regulatory standards, and durability expectations for the built infrastructure. This encompasses compliance with design drawings, construction codes and guidelines, as well as the long-term performance and reliability of the completed facility. Effective CQM practices aim to ensure the final product achieves desired level of quality, functionality, and service life in accordance with stakeholder requirements while exceeding their expectation (Teshome & Gobana, 2018).

2.7.4 Customer Satisfaction

The perception and level of fulfillment experienced by stakeholders, including clients, end-users, and regulatory bodies, the project's overall performance, functionality, and compliance with their expectations and requirements (Neyestani, 2016). This includes factors such as the final product meeting requirements, achieving the desired function and technical quality, and satisfying the needs and preferences of the end-users. Having effective CQM practices can contribute to enhancing customer satisfaction by ensuring the constructed facility aligns with requirements and delivers the expected value.

Incorporating these key project outcome measures can support construction organizations evaluating the impact of their CQM practices and making informed decisions to optimize project success. The following sections analyze the impact of CQM on each of these project outcomes, demonstrating how effective quality management practices contribute to improved project performance.

2.7.5 Impact of CQM on Project Cost

CQM plays a pivotal role in controlling and optimizing project costs. Proper planning, implementation, and control of quality management processes can lead to significant cost savings throughout the project lifecycle. Project costs in construction are affected by multiple factors, including material selection, labor efficiency, rework, delays, and contract variations. Poor quality management often leads to defective work, non-conformities, and cost overruns due to rework and wasted materials. Effective CQM practices, such as detailed Quality Planning, proactive Quality Control, and continuous Quality Improvement, help minimize financial risks and optimize resource utilization.

Based on the study "Effectiveness of Quality Management System on Construction Projects" by Neyestani (2016), a real-world example highlighting the impact of QMS implementation on construction project performance is construction projects in Metro Manila, Philippines. The study found that strict quality management practices, including inspections, material testing, and supplier prequalification, significantly improved project outcomes. The data indicated that contractors who adhered to ISO 9001-based QMS experienced fewer defects, reduced rework, and lower project costs, reinforcing the necessity of a structured quality framework in construction projects (Neyestani, 2016).

Implementing strong CQM practices, such as clear quality objectives, rigorous planning, and strict quality assurance, aligns with Crosby's Zero Defects philosophy, which emphasizes preventing defects rather than fixing them which ensuring efficient project execution, cost control, and long-term infrastructure reliability. This approach is crucial for JSWP, as it can help to reduce costly rework and delays. Contractors who adhere to ISO 9001-based quality procedures experience fewer budget deviations, while those with poor quality management face financial penalties, increased labor costs, and extended timelines. A Zero Defects mindset.

2.7.6 Impact of CQM on Project Schedule

Schedule adherence is a critical factor in project success, as delays can lead to increased costs, contract disputes, and reputational damage. Poor quality management often results in non-conformities, defects, and rework, affecting the project timeline. Quality issues, such as defects, substandard workmanship, and material non-conformities, can lead to significant project delays, rework, and extended construction timelines. The Big Dig project in Boston is a notable example of how poor-quality planning and material failures can lead to significant project delays and cost overruns. Initially estimated at \$2.8 billion with a completion date set for 1998, the project ultimately cost around \$22 billion and was completed eight years later than planned. Issues such as substandard materials and inadequate sealing of tunnels contributed to these setbacks (RICS, 2023).

In JSWP, contractors following structured ITPs and well-defined Quality Assurance procedures experience smoother project execution with fewer unexpected delays. Proactive quality monitoring and timely resolution of issues ensure that construction activities are completed as per the planned schedule, with minimizing the rework and enhancing overall project efficiency. When quality issues are identified early through systematic inspections and audits, corrective actions can be promptly implemented before the material is used, to avoid significant schedule disruptions.

2.7.7 Impact of CQM on Project Quality

CQM is the primary driver for ensuring the desired level of quality in construction projects. Its goal is to ensure that construction projects meet predefined quality standards, durability requirements, and compliance with engineering codes. Effective CQM practices, including quality planning, assurance, and control, are crucial for achieving and upholding the necessary quality standards throughout the project lifecycle. These practices can also mitigate the detrimental effects of poor-quality management, which may result in structural failures, safety risks, and long-term performance problems.

The study by Aichouni *et al.* (2014) on construction projects in Saudi Arabia found that the implementation of a robust quality management system, with a focus on quality control, had a significant positive impact on the overall quality of construction projects. The authors highlighted that the strict adherence to quality control measures, such as

regular inspections, material testing, and monitoring of construction processes, led to a reduction in defects, improved workmanship, and enhanced customer satisfaction. Similarly, a case study on a stormwater network project in the UAE conducted by Hamdan (2024) emphasized the critical role of implementing CQM practices to meet required standards and customer needs.

These studies align with the needs of JSWP, as quality can be achieved through strict compliance with QMS, especially ISO 9001 standards. The implementation of CQM practices, such as compliance with industry standards, product certifications, and regular third-party inspections, helps ensure the quality and durability of critical infrastructure components, such as water pipes, precast manholes, and marine outfalls. Contractors that prioritize quality management ensure that their structures withstand environmental conditions, minimize maintenance costs, and function efficiently for decades, and as a result contributing positively to sustainability.

2.7.8 Impact of CQM on Customer Satisfaction

Customer satisfaction in construction is not limited to end-users and project owners but also includes regulatory bodies, local authorities, and environmental agencies. Effective CQM is a crucial factor in enhancing customer satisfaction in construction projects. A well-executed project that adheres to quality standards and meets deadlines, within budget, contributes to higher stakeholder confidence and client satisfaction.

Expo 2020 demonstrates that effective CQM is not just about building infrastructure but also ensuring that quality management enhances user satisfaction, safety, and sustainability. The clear planning, strict assurance measures, and continuous improvement strategies used in Expo 2020 reflect CQM principles, proving that well-managed construction quality leads to higher customer satisfaction. A survey conducted revealed that 95% of visitors to the Terra Pavilion pledged to adopt sustainable practices, demonstrating the impact of high-quality infrastructure and engaging experiences on public behavior. Additionally, the event's stringent health and safety protocols, including the "Dubai Assured" certification, ensured a safe experience for over 24 million visitors, further reinforcing how proactive quality management fosters trust, enhances user experience, and stakeholder expectations.

In the context of JSWP, the implementation of robust CQM practices including regular site inspections, material testing, and quality audits has played a crucial role in ensuring that infrastructure projects meet the expectations of local authorities, environmental agencies, and the public. However, quality issues and rework can contribute to project delays, leading to prolonged road closures and disruptions to daily life for citizens. Since the local community is a key stakeholder in JSWP, extended construction timelines can result in traffic congestion, accessibility challenges, and public dissatisfaction. While effective quality management practices aim to minimize such disruptions, unforeseen defects or inefficiencies may still delay project completion and impact residents. Therefore, contractors must carefully balance rigorous quality control with efficient project execution to mitigate inconveniences and uphold public confidence in large-scale infrastructure improvements.

2.7.9 AI as an enhancer of CQM

In the context of construction quality management, the value of AI lies in its ability to convert quality-related data into timely, actionable insights. Instead of treating quality planning, assurance, control, and improvement as separate manual activities, AI can support a more connected quality management cycle by linking historical records, inspection results, non-conformance data, audit findings, and lessons learned. This allows quality teams to identify patterns earlier, improve monitoring accuracy, support preventive actions, and make more informed decisions across the project lifecycle.

In large infrastructure projects, where multiple stakeholders, fragmented systems, and recurring site issues often reduce the effectiveness of traditional CQM practices. AI can provide additional analytical support and enhance quality planning through historical data analysis, predictive risk identification, support quality assurance through digital audits and compliance monitoring, improving quality control using real-time inspection data and detection, and quality improvement through AI-assisted root-cause analysis, lessons learned, and preventive action mechanisms. Table (2-1) below summarizes how AI technologies can enhance the four primary dimensions of CQM.

Table 2-1: AI Technology enhancement for current CQM practices

CQM Dimension	Current traditional Practice	AI enhancement
Quality Planning	Manual plans, Historical risk-based planning	Predictive analysis, BIM integrated planning, historical data analysis, and AI-supported quality risk identification
Quality Control	Manual checklists, visual inspections, testing records, and spreadsheets-based tracking	Computer vision, drone inspection, sensors, Image recognition, mobile supported inspection applications, and automated defect detection
Quality Assurance	Periodic audits, site walkthroughs, management reviews, and compliance checks	Real time dashboards, automated compliance monitoring, anomaly detection, predictive analysis, triggers warnings, AI-supported audits, reports and MOMs analysis
Quality Improvement	Post-completion lessons learned, and manual root cause analysis	Pattern recognition, AI-supported root-cause and recurring defect analysis, predictive prevention, and lessons-learned analytics

AI-enhanced Pyramid of Quality shown in Figure (06) illustrates how digital intelligence can act as an operational enhancer within CQM. The figure positions AI as a supporting layer that strengthens the traditional quality pyramid by enhancing planning, assurance, control, and improvement activities. This does not suggest that AI automatically replaces traditional quality management or immediately becomes a structural moderator. Rather, it represents a progressive pathway in which AI first supports existing CQM practices and, with sufficient digital maturity, integrated data platforms, and governance readiness, may eventually contribute to a more advanced Quality 4.0 based quality governance system.

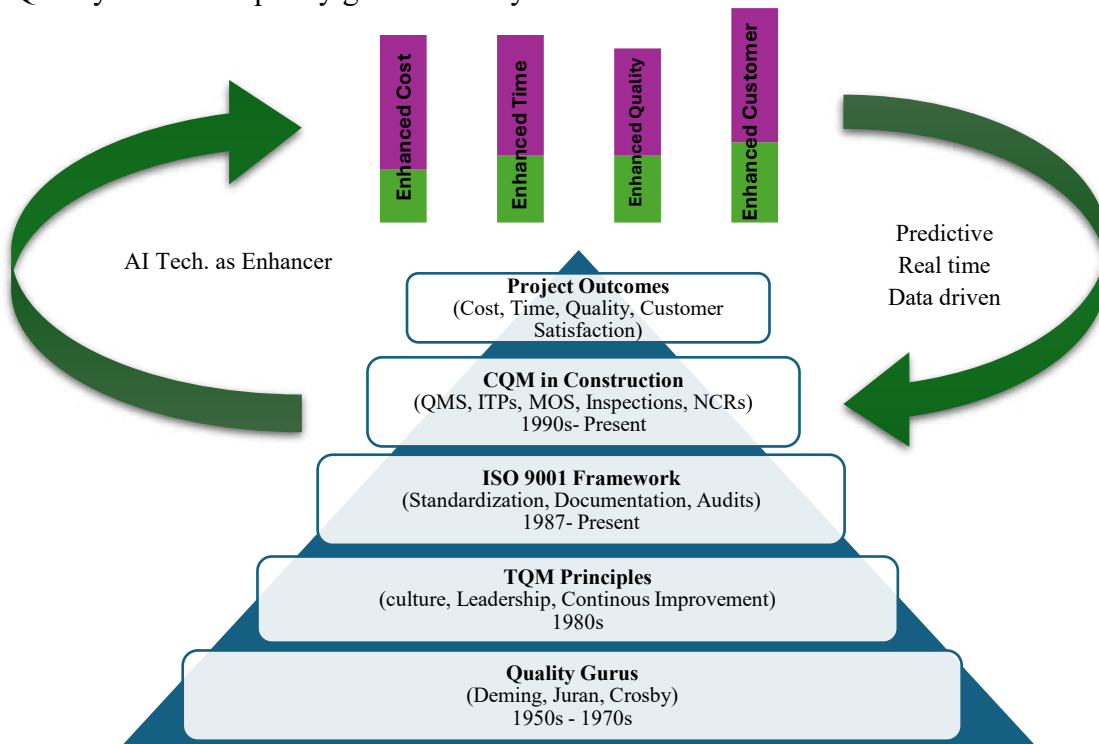


Figure 06: AI-Enhanced Pyramid of Quality within a Quality 4.0 Perspective
Source: Prepared by the author

Figure (06) presents the AI-enhanced Pyramid of Quality as Quality 4.0 oriented extension of the traditional quality pyramid presented earlier in this chapter. It shows the integration relationship between CQM practices, AI technologies, and project outcomes. AI applications such as predictive analytics, real-time monitoring, automated defect detection, and data-driven decision support are positioned as an enabler that enhances each CQM function. In this sense, AI is visualized not as an isolated tool, but as an operational enhancer that strengthens the quality management ecosystem and supports improved cost, time, quality, and customer satisfaction outcomes in large-scale infrastructure projects such as JSWP.

2.8 Research Gaps

The literature review has highlighted the significant impact of Construction Quality Management on the various aspects of project performance, including cost, schedule, quality, and customer satisfaction. Although the existing body of research provides valuable insights into the importance of CQM, the effectiveness of CQM systems becomes insufficient as the scale and complexity of projects increase. There is a need to further explore the potential of emerging technologies, such as Artificial Intelligence, to enhance the effectiveness of CQM practices and improve overall project outcomes.

Also, the reviewed literature suggests that AI-powered technologies, such as automated inspections, predictive analytics, and workflow optimization, can significantly improve the efficiency and accuracy of quality management processes. Furthermore, AI-enabled real-time monitoring and decision support systems can empower project teams to identify and mitigate quality issues proactively, reducing the risk of rework, delays, and cost overruns. However, these research often focuses on isolated applications of AI in quality management, without addressing its holistic, systematic impact on overall CQM practices and project performance.

Furthermore, extensive research has been conducted on CQM and its impact on project outcomes. Several gaps remain, particularly in the context of large-scale infrastructure projects like JSWP and the adoption of advanced quality management technologies.

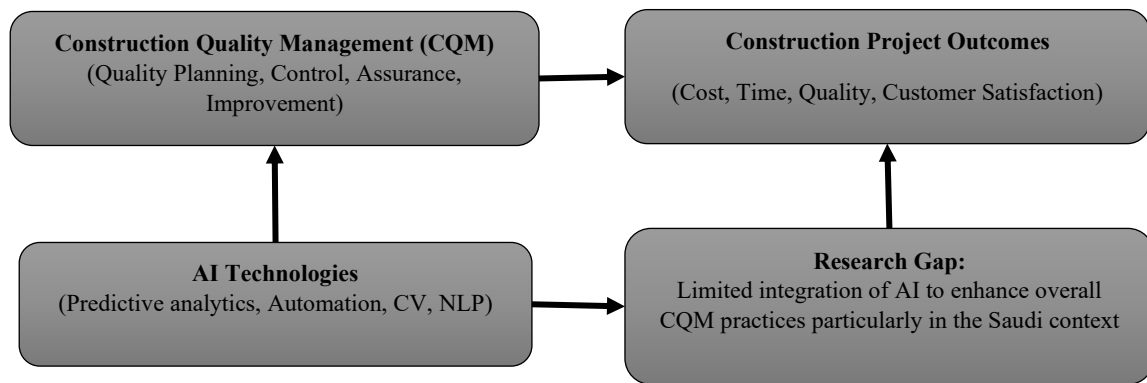


Figure 07: Gap in Literature – The Moderating Role of AI on the Relationship Between CQM practices and Project Outcomes.

Source: Prepared by the author

The key research gaps identified from literature include as illustrated on Figure (07):

- **Limited Studies on CQM in Large-Scale Infrastructure Projects in Saudi Arabia:** While the existing literature provides a general understanding of CQM and its implications, there is a lack of research specifically focused on the challenges and best practices of implementing CQM in large-scale infrastructure projects within the Saudi Arabian context. Existing studies on CQM focused on residential, commercial, or small-scale construction projects, with limited research specifically addressing the challenges and best practices of CQM in large-scale infrastructure projects, particularly in the Saudi Arabian context. There is a lack of empirical data on how ISO 9001-based QMS frameworks perform in programs like JSWP and their effectiveness in mitigating quality risks, cost overruns, and schedule delays.
- **The Need for a Deeper Understanding of CQM's Direct Impact on Project Outcomes:** While studies confirm that quality management improves project performance, there is limited quantitative research on the degree of impact each dimension of CQM on cost, schedule, quality, and customer satisfaction. However, as the complexity and scale of projects increase, such as in JSWP, more in-depth analysis is needed to understand the relative importance and interrelationships between various CQM practices and their direct impact on project outcomes.
- **Challenges in Implementing ISO 9001 in Multi-Contractor Infrastructure Projects:** The literature highlights the challenges faced by construction firms in effectively implementing ISO 9001-based quality management systems, particularly in large, complex projects with multiple contractors and subcontractors. The lack of a unified, collaborative approach to quality management across the supply chain often leads to inefficiencies, inconsistencies, and quality issues.

- Further research is needed to identify best practices and strategies for implementing robust CQM frameworks in multi-stakeholder infrastructure projects, especially in the context of the Saudi Arabian construction industry. Although project requirements at JSWP strictly adopt ISO 9001, more investigation is needed to evaluate how ISO 9001 compliance is interpreted and applied differently by contractors and whether it is truly integrated into their daily quality processes or treated as a procedural requirement.
- The Role of Emerging Technologies in Enhancing CQM Practices: The existing literature often emphasizes the general advantages of AI in construction, such as its impact on a specific project outcome or its application to specific quality management issues. Studies acknowledge the potential of individual technologies like AI, BIM, and IoT to address specific quality management issues such as inspections, defect detection, and workflow optimization. There is a lack of empirical research on the systematic integration and holistic impact of these technologies on overall CQM effectiveness and project performance. This research aims to provide a more comprehensive understanding of how emerging technologies can enhance the implementation and impact of quality management systems in large-scale infrastructure projects.

Recent exploratory research on the adoption of Artificial Intelligence in the Saudi construction industry provides valuable empirical support for the gaps identified in this literature review. In a targeted survey of 60 construction industry professionals, Ujaimi et al. (2024) confirmed several key barriers to AI implementation, including technical limitations, high costs, lack of skilled personnel, regulatory ambiguity, and resistance to change. These challenges reflect the limited digital readiness of many construction firms and expose the operational and organizational weaknesses in current CQM systems. The findings suggest that existing quality practices are often not strong enough to support or integrate advanced technologies, particularly in large-scale infrastructure projects involving multiple stakeholders, like those under JSWP.

This study thus functions as a pilot investigation, confirming not only the presence of barriers to AI adoption but also the underlying deficiencies in the implementation of systematic quality practices. By identifying these real-world challenges, such as the absence of standardized digital platforms, insufficient training on quality tools, and

fragmented quality data, the research underscores the urgency of rethinking how CQM can be enhanced through technological integration. These insights validate the need for deeper academic inquiry into the moderating role of AI in strengthening CQM practices and improving project outcomes.

To address the identified gaps, a multi-layered approach is suggested to improve the implementation of CQM in large-scale infrastructure projects. First, management-level engagement should be enhanced by incorporating quality objectives into strategic plans and performance evaluations. Second, training programs and workshops should be established to increase quality awareness and capability among project teams, particularly in ISO 9001 application and CQM tools such as ITPs and NCRs. Third, project owners should encourage the use of integrated digital platforms for real-time quality tracking, documentation, and inter-contractor coordination. This includes adopting AI-enabled tools for predictive defect detection, automated submittal reviews, and workflow optimization, which can improve the effectiveness and responsiveness of CQM practices across complex, multi-stakeholder environments like JSWP.

Despite growing interest in the application of AI in construction, existing research has yet to fully explore its role as a moderator between CQM practices and project outcomes. This opens an important research opportunity: understanding how AI integration into Quality Planning, Control, Assurance, and Improvement can elevate the efficiency and impact of CQM. This study aims to address this gap by examining the moderating effect of AI technologies on the relationship between CQM and project outcomes within the context of the Jeddah Stormwater Program. The next chapter will build on these findings by introducing a conceptual framework and research methodology designed to evaluate the interaction between AI technologies and quality management systems in the context of JSWP.

2.9 Conclusion of the Literature Review

This chapter has provided an extensive review of CQM and its impact on key project outcomes, focusing on Quality Planning, Quality Control, Quality Assurance, and Quality Improvement as the four core dimensions of CQM. The literature has demonstrated that effective quality management strategies lead to reduced cost overruns, fewer schedule delays, improved project durability, and higher stakeholder

satisfaction. On the other hand, the literature highlighted several key barriers to the successful implementation of quality management in the construction industry, including issues with inconsistent application of quality practices, the inherent complexity and variability of construction work, and broader challenges within the industry itself.

The analysis also revealed that while CQM principles are well-established, their implementation varies significantly depending on contractor commitment, technological integration, and project-specific challenges. In the JSWP, ISO 9001-based quality management systems provide a structured approach to ensuring defect-free execution, but the effectiveness of these systems depends on how well contractors integrate them into their daily operations.

Despite the well-documented benefits of CQM in construction, several research gaps remain, particularly regarding its impact on infrastructure projects in Saudi Arabia, its role in reducing project risks, and the integration of advanced digital quality management tools. Addressing these gaps through empirical research will help refine the best practices, improve policy recommendations, and enhance the long-term effectiveness of quality management in large-scale infrastructure projects.

This literature review establishes the foundation for the next phase of the research by supporting the study hypothesis in three main directions. First, the literature shows that large and complex infrastructure programs place significant pressure on traditional CQM practices due to multiple stakeholders, fragmented workflows, many concurrent activities, and recurring quality issues. Second, prior studies indicate that AI-driven CQM practices may enhance quality through predictive analytics, automated monitoring, defect detection, risk escalation, and data-driven decision making. Third, the reviewed literature identified financial, organizational, technical, and ethical barriers that may limit the effective integration of AI into CQM systems. Accordingly, the next phase of the research focuses on analyzing how CQM dimensions influences project outcomes in JSWP and exploring how AI can support the optimization of quality practices for improved project performance.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Overview

This chapter outlines and explains the research methodology employed in the study to provide a clear understanding of the framework used. The research seeks to examine the relationship between Construction Quality Management practices and project outcomes, and how the relationship might be 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

3.2 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 are given equal priority, and the results are brought together during interpretation using triangulation strategy, where selected qualitative themes are used to support, contrast, or elaborate on the quantitative findings.

Figure (08) 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 JSWP case, ensuring methodological transparency and coherence.

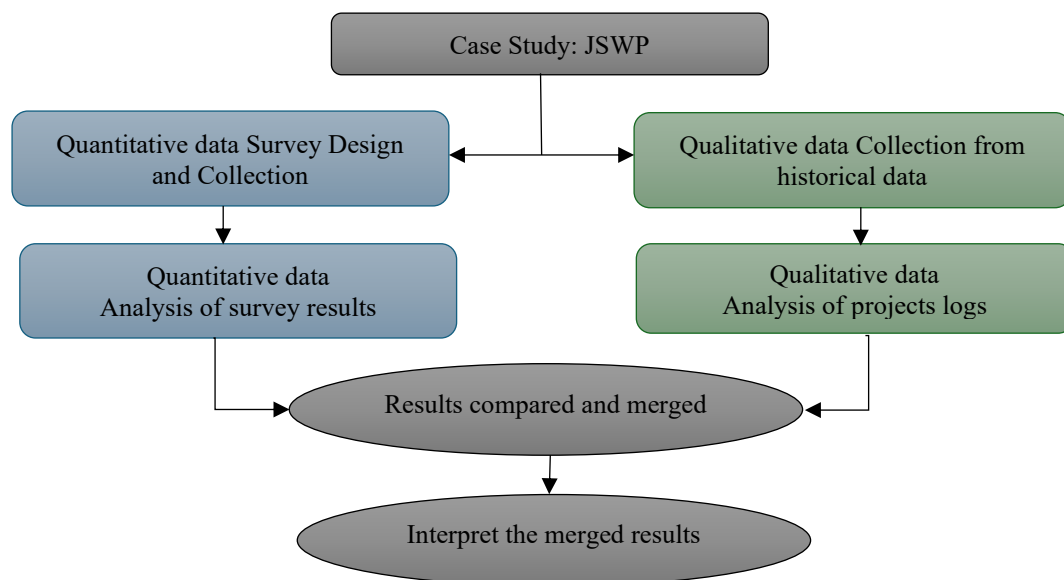


Figure 08: Procedural Flowchart of the Convergent Mixed Methods Case Study Design
Source: Inspired by Creswell and Plano Clark (2017, p. 119)

3.3 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 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.

3.4 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 program 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 AI.

Given the program's complexity and the need to capture insights from relevant stakeholder groups, the study adopted a purposive, non-proportional stratified sampling strategy. This approach was appropriate because the research required participants with direct knowledge of CQM, infrastructure project delivery, project outcomes, or AI-related Practices. The purposive element ensured that respondents were selected based on their relevance to research topic, while the non-proportional stratified element ensured that key stakeholder groups were represented without requiring each group to reflect its exact proportion in the overall population.

The target population included population included professionals involved in infrastructure projects in the Western Region of Saudi Arabia, with particular emphasis on JSWP. The sampling frame included project managers, quality managers, QA/QC professionals, engineers, site supervisors, inspectors, contractors / sub-contractors, consultants, suppliers, and supporting project disciplines. The groups were selected because they are directly involved in quality planning, quality assurance and control, quality improvement, project delivery, and decision-making processes related to construction project outcomes.

To estimate the minimum required sample size (n_0), Cochran's formula was applied for a finite population. Assuming a 95% confidence level ($Z = 1.96$), a 5% margin of error ($e = 0.05$), and a 50% response distribution ($p = 0.5$), the formula is as follows:

$$n_0 = \frac{Z^2 \times P \times (1 - p)}{e^2} = \frac{(1.96)^2 \times 0.5 \times 0.5}{0.05^2} = 384.16$$

Since the target population (N) is estimated at 3,000 individuals across the infrastructure sector in the Western Region, the adjusted sample size (n) was adjusted using the finite population correction (FPC):

$$n = \frac{n_0}{1 + \frac{n_0 - 1}{N}} = \frac{384}{1 + \frac{383}{3000}} \approx 353$$

As per the result above, the final sample size was increased to 500 participants to enhance representatives of the sample and to account for expected non-response, incomplete responses, and unusable submissions. This target was also intended to increase the participation of groups most relevant to the study, particularly quality professionals, and align with established mixed-method research practices that prioritize analytical depth over strict proportionality.

A total of 190 survey respondents filled in the questionnaire, of which 167 valid responses were retained after excluding 23 incomplete or inconsistent ones. Although this sample was below the initial target, it was considered adequate for the exploratory convergent mixed-methods case study. The valid responses supported the quantitative analyses reported in chapter Four, while triangulation with project records, NCRs, SORs, MOMs, and AI-assisted analytical outputs strengthened the findings.

3.5 Instrumentation

Given the mixed-methods approach explained earlier in this chapter, the study employs two primary instruments to gather comprehensive data: a structured questionnaire for the quantitative phase and document analysis for the qualitative phase. The 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 reports, meeting minutes, and progress updates, providing contextual insights to complement & validate quantitative data obtained through the questionnaire.

3.5.1 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 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 - This section assesses the current practices and perceived effectiveness of Construction Quality Management (CQM) as the independent variable of the study. The first part covers the presence and application of quality management tools, including quality management systems (QMS), KPIs, dashboards, manual reports, ISO certifications, and procedures for managing defects and ensuring compliance. Respondents evaluate their use of these tools and the challenges they face in maintaining quality—such as early defect identification, corrective actions, and workforce training, using Likert 5-scale ratings. The second part includes structured statements designed to measure the effectiveness of key CQM dimensions: Quality

Planning, Quality Assurance, Quality Control, and Quality Improvement. These items assess how current quality practices influence project success in terms of cost, schedule, quality, and client satisfaction.

Section C –Represents the dependent variable of the study. It focuses on the perceived impact of quality practices on four critical project outcomes: cost, time (schedule), quality of delivered work, and customer satisfaction. Respondents rate their agreement with a series of Likert 5-scale statements reflecting how effectively the current quality management efforts contribute to achieving these outcomes. The section serves to link the effectiveness of CQM practices, as perceived by stakeholders, with tangible project performance dimensions.

Section D – Artificial Intelligence (AI) in Quality Management: This section reflects the moderating variable of the research. It explores the current state of awareness, readiness, and expected benefits of integrating AI technologies into construction quality practices. Participants evaluate the extent to which AI can support quality planning, defect detection, real-time monitoring, data analysis, decision-making, and continuous improvement. The section also includes Likert-based items assessing perceived challenges in AI adoption, such as cost, skills, ethical concerns, and integration complexity, as well as enabling factors like management support and training. These insights aim to clarify how AI might strengthen the link between CQM and improved project outcomes in complex infrastructure projects.

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 deployment, questionnaire was reviewed for content validity, and a pilot test was conducted to assess reliability, clarity, and time efficiency, and revisions were made accordingly.

3.5.2 Qualitative instrument

For the qualitative component, the study analyzed historical quality documentation, primarily NCR, SORs, Logs, MOM, and dashboards, all obtained from completed and ongoing infrastructure projects within JSWP during the period from 2021 to 2025. These documents offer direct evidence of recurring quality issues, contractors' performance patterns, and procedural gaps, enabling deeper insight into the practical challenges of current CQM practices in large-scale infrastructure projects.

Document analysis helps to enable the examination of real projects, governance records and operational data, which offer deeper insight into the practical challenges associated with CQM in large scale infrastructure programs. This qualitative evidence complements the survey findings by providing context for statistical trends and uncovering underlying patterns not easily captured through questionnaires. Qualitative data undergo thematic coding and categorization to identify key themes, including contractors' non-compliance, workmanship issues, inspection failures, coordination challenges, material issues, effectiveness of quality interventions, CAPA and quality improvement efforts, and coordination challenges.

During the data analysis stage of qualitative data, Manus AI was utilized by integrating them into dashboards to enhance analytical capabilities. Historical NCR and SOR logs, MOMs, and other reports were digitized and processed using Natural Language Processing (NLP) techniques to assist in the classification and organization of textual data, enabling efficient identification of recurring quality-related themes and patterns. The integration of AI-supported analysis enhances the study's ability to process complex project records and contributes to the development of a data-driven framework aimed at strengthening Construction Quality Management practices and improving infrastructure project outcomes.

3.6 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 within Saudi Arabia. Given the use of mixed-methods convergent design, steps were taken to address both quantitative and qualitative standards of research rigor.

3.6.1 Quantitative Part

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

In addition to expert review, construct validity was 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, is mapped to specific research constructs to ensure conceptual coherence and measurement accuracy. The instrument captured the four dimensions of CQM, alongside project outcomes (cost, time, quality, and stakeholder satisfaction) as the dependent variable. The moderating role of AI was reflected in items measuring application level, awareness, perceived impact, and organizational readiness. To further assess convergent and discriminant validity, structural model testing is conducted using SmartPLS.

Furthermore, face validity is assessed through pilot testing with a small sample of 20 professionals representing target population for evaluating wording, structure, and usability of the questionnaire. Their feedback guided revisions for clarity & reliability. Established measures for constructs such as CQM practices, project outcomes, and AI adoption were incorporated to strengthen validity (Mitra & Tan, 2012).

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

3.6.2 Qualitative Part

To ensure the dependability of the qualitative analysis, this study applied 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 JSWP.

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

3.7 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 work, and stakeholders / 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 is also contextualized using qualitative analysis of historical project data and digital quality logs, particularly where AI integration may support prediction or pattern recognition.

Therefore, in this study AI is treated as a moderating variable rather than a mediating one. A moderating variable affects the strength or direction of the relationship between an independent variable and dependent variable. The study objective is to examine whether AI strengthens or modifies the relationship between Construction Quality Management Practices and Construction Project Outcomes. In contrast, a mediating variable would explain the mechanism through which CQM affects project outcomes. Since the objective of this research is to explore whether AI changes the strength of the CQM and Project outcomes relationship, the appropriate term used throughout the study is moderating variable.

3.8 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 on project outcomes and the moderating role of Artificial Intelligence within infrastructure projects, using JSWP as the case context.

3.8.1 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- 5 scale was used for quantification, and confidentiality of all participants was maintained. Data collection phase is designed to reflect diverse roles (e.g., engineers, managers, consultants, contractors), project phases to capture view of the quality landscape.

3.8.2 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 within JSWP. The records span several project phases and involve multiple contractors 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.

3.8.3 Additional Qualitative Source: Meeting Minutes

In addition to formal documentation, this study incorporates insights from weekly technical meetings and client progress meetings, which served as an interactive forum for stakeholders to review project performance, discuss emerging quality challenges, and propose corrective measures. These sessions, involved 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, recurring and trending quality issues, and CAPA. These findings were later compared to survey data and document analysis for triangulation.

AI technologies were used to analyze patterns in 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.

3.8.4 Data Collection Matrix

Table (3-1) below provides 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 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.

Table 3-1: Data Collection Matrix aligned with research questions				
Research Question	Data Source	Type of Data	Collection Method	Analysis Approach
Research Q1: CQM insufficiency & its impact on project outcomes	Questionnaire Section B	Quantitative Likert scale, and open question	Structured Questionnaire (Stakeholders)	Descriptive Statistics, SEM (SmartPLS)
	NCR & SOR Logs from JSWP Projects	Qualitative Documents Analysis (NCR/SOR, MOM)	Collection of archived documents	Thematic Analysis (CQM dimensions)
Research Q2: AI-driven CQM modifies impact of CQM on project outcomes	Questionnaire Sec. B & C Open-ended Responses MOM	Quantitative	Structured Questionnaire	Moderation Analysis via SmartPLS
		Qualitative	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 & perception MOM	Quantitative	MOM	Frequency Analysis
Source: Adapted from Creswell & Plano Clark, 2017				

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 shown in (Figure 09) visually shows the logical connections between research questions, data sources, and analysis pathways, emphasizing the integrated nature of the research process.

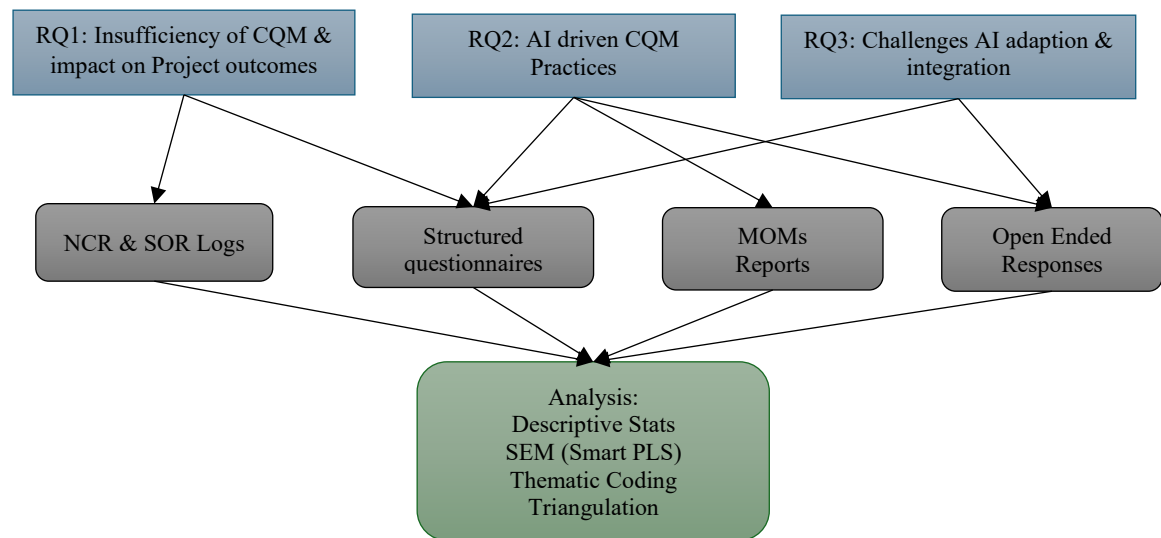


Figure 09: Concept map Linking Research Questions, Data Sources, and Analysis Methods
Source: Adapted from Creswell & Plano Clark, 2017

3.9 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.

3.9.1 Quantitative Data Analysis

Quantitative data from the structured questionnaire were 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) was 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 were examined through composite reliability, AVE, and discriminator validity. Respondents from contractor organizations were asked to identify the specific JSWP project(s) they are involved in, enabling project-level linking of survey responses and corresponding NCR/SOR data for deeper case-based analysis (Creswell & Plano Clark, 2017, p.72).

3.9.2 Qualitative Data Analysis

Qualitative data was 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 was employed, involving open coding, categorization, and theme development aligned with the CQM framework. Manual coding is supported by AI-based Natural Language Processing (NLP) tools using Manus AI to improve scalability and reduce bias by detecting patterns, clustering keywords, and forecasting quality risks. To ensure dependability, the analysis followed a documented and replicable coding framework to maintain consistency. Themes related to AI readiness and adoption were extracted to complement quantitative findings (Creswell & Plano Clark, 2017, p.75).

3.9.3 Data Integration Strategy

After independent analysis, findings were merged for triangulation to identify convergence, divergence, and complementarity between the two strands. Where feasible, qualitative themes were transformed into frequency counts to support comparison, and joint displays 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 strengthens internal validity. Conversely, discrepancies were interpreted in light of project complexity and organizational readiness for AI. The integrated insights informed the development of an AI-enhanced CQM model, supporting practical recommendations for improving quality performance in large-scale infrastructure programs.

3.10 Model Development Plan

As part of the future development phase of this research, Artificial Intelligence techniques are explored to support and enhance the CQM Practices within infrastructure projects. Within the study, AI based models that provide AI-assisted analytical tools were utilized to process and examine large volume of project documentation during the qualitative data analysis stage. These tools supported thematic extraction from project records such as NCRs, SORs, MOMs, and progress reports. 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 involved collecting and preparing existing data sources from completed projects, particularly those within JSWP. These include NCRs, SORs, project profiles, and performance dashboards. Additional insights also derived from the survey data, particularly where participants discuss challenges and opportunities in applying AI to quality management. The integration of NLP techniques enabled the systematic analysis of textual project data within historical and ongoing projects documents, to identify recurring quality related themes and patterns, and overall program performance. This approach assisted the research in identifying systematic quality issues and governance challenges within JSWP, which complement the quantitative survey analysis conducted during the study.

Beyond the analytical role applied within the research, the findings also supported the conceptual development of an AI-enabled framework aimed at strengthening CQM practices. The proposed framework explores how machine learning and predictive analysis could be used to analyze historical project datasets, detect emerging risk patterns, while supporting proactive decision-making and project quality governance.

Further development of such an AI model involved integrating project quality logs, NCR and SOR records, and program progress reports and meetings outcomes into cloud based analytical environments. Platforms such as Microsoft Azure or Google AutoML offer capabilities for data integration, predictive analytics, and real time visualization through tools such as power BI dashboards. All in which can help in transferring projects data into insightful information that can help management to capture the overall view of the projects and identify risks early.

Initial AI applications focus NLP processing techniques for automated classification of quality issues and identification of recurring defects patterns. Subsequently, supervised learning models were explored to predict potential quality risks or detect early indicators of contractor non-compliance based on projects historical data.

The AI framework proposed in this study therefore represents a conceptual step toward integrating intelligent data analytics into traditional quality management systems. This approach aligns well with the principles of Quality 4.0, which emphasizes the use of advanced digital technologies including AI, big data analytics, and automation to enhance quality management practices. This can be also adopted within the

infrastructure sector and supports the transition from traditional reactive quality monitoring toward data driven quality intelligence. It can also support organizations to detect risks earlier and strengthen governance over complex construction programs. The results of the AI-assisted document analysis and the identified thematic patterns are presented in Chapter Four, where they are triangulated with the quantitative findings of the study.

CHAPTER FOUR

RESEARCH RESULTS

4.1 Introduction

This chapter represents the results of the study “Exploring the Moderating Role of Artificial Intelligence on the Impact of Quality Management on Construction Project Outcomes. The chapter provides a comprehensive account of both quantitative and qualitative findings derived from the mixed-methods design described early on Chapter three, which 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 similar projects within Saudi Arabia. The analysis included 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, while following the procedures recommended by Hair et al. (2021).

Section 4.2 presents quantitative data analysis, including response rate, demographic profile, and the results of statistical tests for each hypothesis. Section 4.3 shows qualitative analysis, integrating themes emerging from program documents, while Section 4.4 synthesizes both quantitative and qualitative strands to present the merged interpretation. At the end of the chapter, section 4.5 concludes with the summary of findings and its link to the research objectives. Combining this analysis provides 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 through the survey. A total of 190 responses were initially received. During the data screening process, 23 responses were excluded due to incompleteness, low completion quality, or inconsistent response patterns. Therefore, 167 valid responses were retained and used for the final quantitative analysis.

The analysis follows the structure defined in Chapter Three and covers descriptive statistics, reliability and validity testing, correlation analysis, regression analysis, and moderation testing. Unless otherwise stated, the quantitative analysis reported in this chapter are based on the final 167 valid survey responses. The moderation analysis was conducted to assess the role of Artificial Intelligence as a moderating variable in the relationship between Construction Quality Practices and construction project outcomes. Accordingly, the interaction term between CQM and AI was tested to determine whether AI has a statistically significant moderating effect. This analysis does not test mediation, as AI was not examined as an intervening mechanism between CQM and project outcomes.

4.2.1 Statistical Techniques and Analysis Procedures

After the survey data were screened and the final 167 valid responses were retained, the dataset was coded and analyzed using IBM SPSS version 25. The analysis was conducted 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.

4.2.2 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, which 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.

4.2.2a Reliability and validity for Independent Variables (CQM)

Table 4-1: Validity & 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), higher than the acceptable threshold of 0.70, indicating a high level of reliability."

4.2.2b Reliability and validity for Moderating Variables (AI)

Table (4-2) 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**	0.855	
AI1	0.650**		
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 with overall Cronbach's Alpha value reached (0.852), which is higher than acceptable threshold of 0.70, indicating that the scale demonstrates high level of reliability."

4.2.2C 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**	0.712	
Quality2	0.756**		
Quality3	0.778**		
Quality4	0.755**		
overall project quality	0.798**		
Customer Satisfaction1	0.692**	0.781	
Customer Satisfaction2	0.753**		
Customer Satisfaction3	0.853**		
Customer Satisfaction4	0.816**		
customer satisfaction	0.853**		
** A function at the level of significance less than (0.01)			

Table (4-3) presents the validity coefficients (Pearson Correlation Coefficients) and reliability coefficients (Cronbach's Alpha) for 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."

4.2.3 Respondents' Demographic Information

Table (4-4) below shows the Descriptive Analysis of demographic characteristics of the study sample regarding the respondents.

Table (4-4) 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 experience do you have?	0 - 5 Years	12	7.2
	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
	Medium 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
	Medium 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 above table (4-4) and Figure (10) present 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: highest representation was for Senior Engineers at 31.2%, with 49 respondents, the lowest was for Inspectors at 3.8%, with 6 respondents.
- Department: construction department had the highest representation at 27.5%, with 46 respondents, and the Planning/Cost Control department had the lowest representation at 4.8%, with 8 respondents.
- Role of the Organization: the highest representation was for PMO/PMC at 31.1%, with 52 respondents, lowest 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, and 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.

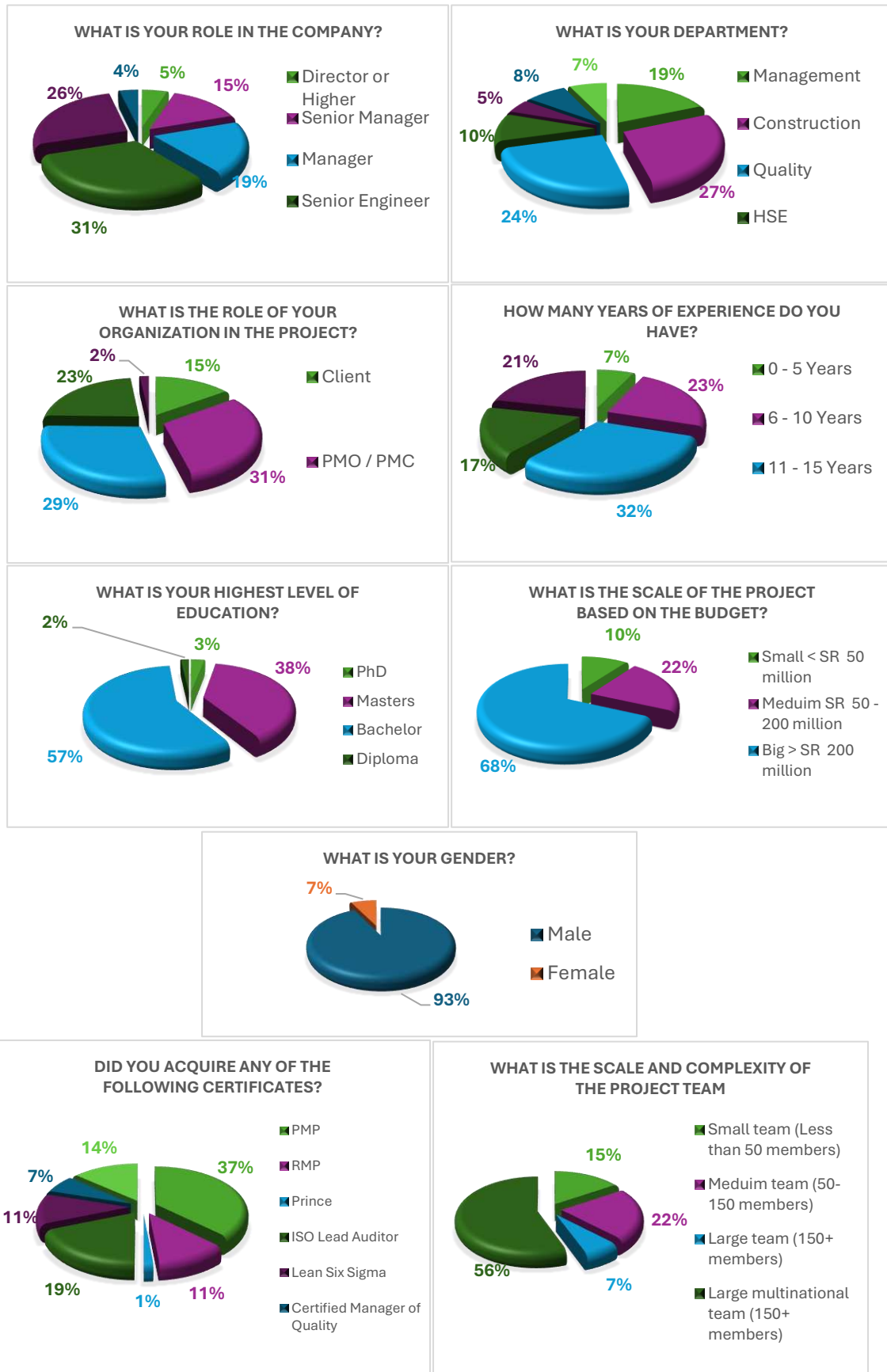


Figure 10: The demographic characteristics of the study sample, showing the percentage of respondents in each category

4.2.4 Open-ended questions related to part A – PM Background & Experience

Table (4-5) Responses to the Question (Did you acquire any of the following certificates?) (Other (please specify))	Table (4-6) Responses to the Question (If working on the Jeddah stormwater program please include the project name for analysis purposes?)
Responses	Responses
Approval from client specially for inspectors	AFAH
Building concertation specialist KUL K (Swe RISE)	AL FIRDOUS
Certified protection professional from ASIS	Al Hamdaniya
CLAC	AL-Falah and AL-Hijaz
Consultancy	Albasteen
Digital Transformation in Construction and Engineering Projects n	Alhamra project
FMP	Alsawari
Grc	Aproq alrogham
GRC	Client Representative as PMO
GRCP, GRCA, CCQM, CQA, CISSP, CISA	Drainage Solutions for Al-Hamdaniya District
Igc	I am working on other area at consultants office for facility management
IOSH	Jeddah Storm Water Program
IPMA D	JSWP
ISO 9001 TO 2015 CERTIFIED	N/A
MPM	None
Nebosh	Northern Channel Project
NEBOSH IGC	old makkah rd
Non	PMCM
Ongoing study for ISO Lead Auditor	PMO in 2018 under WorleyParsons
OSHA	PMO Team
OSHA, NEBOSH	Rawdah
PCQM	SOUTH OBHUR
Pgmp, PfMP	south projects
PMI-SP	South ubher
PMOCP	storm drainage project Almarwah
PMS (Performance Management System audit)	SWRI & YAQT
Primavara	WSP - all projects in the program of JSWP
Quality assurance of concrete	Management and Supervision Office Consultant
Resolving project disputes	Supervision of Stormwater Drainage Network Maintenance Projects
SCE	Al-Ruban, Al-Hamdaniah, Al-Falah, Al-Hijaz, Al-Salhiah, Al-Rahmaniah, Taybah
Value engineer	Al-Sawari, Al-Yaqout, KFRD, South Obhur
Safe	Al-Firdous
None	Previous Experience: Yes, Riyadh
	All Stormwater Drainage Projects Under Implementation

4.2.5 Construction Quality Management subjects

Table (4-7): 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	``	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 (4-7): Distribution of the study subjects according to Construction Quality Management “CQM”				
Construction Quality Management “CQM”	Min-Max	Mean ± SD	median	Mean score percent
Inspection and test results are reviewed and analyzed to identify trends and recurring issues	1-5	3.75±0.84	4.00	75.09%
Coordination occurs between site engineers, QA/QC staff, and contractors to resolve quality issues	1-5	3.86±0.83	4.00	77.13%
Quality Improvement				
Quality procedures are reviewed and updated regularly	1-5	3.80±0.88	4.00	75.90%
There are effective mechanisms for capturing feedback and lessons learned	1-5	3.56±0.95	4.00	71.27%
Training programs on quality standards are provided continuously	1-5	3.49±0.99	4.00	69.70%
Corrective and preventive actions (CAPA) are actively implemented and monitored	1-5	3.65±0.81	4.00	72.93%
Quality performance data is analyzed periodically to identify improvement opportunities	1-5	3.59±0.93	4.00	71.81%

The table (4-7) 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 CAPA 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 QMSs.

4.2.5a 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 lowest means were stakeholder involvement and lessons learned (3.49, ~69.7%), showing potential for improving engagement & organizational learning.

4.2.5b Quality Assurance

- Means ranged 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.

4.2.5c 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 lowest was for timely correction of NCRs (3.66, 73.25%).
- It reflects effective QC processes, with room to improve speed of issue resolution.

4.2.5d 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.

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

Table (4-8) below shows the response to Question 14 - used tools for CQM

Table (4-8) 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 accessible for every eng in our project.	
Dropbox cause it has access for everyone	
Enterprise software can help in transforming the industry	
Excal & 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 , becace 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 scalability 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 onfidentiality.	
Sharepoint, MS Project, PrimaVera	
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 (4-9) below shows the response to Question 15 (Please describe any specific challenges faced in implementing or improving quality practices?)

Table (4-9) 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 spped the work and minimise paper work waste	
Improper communication between team members	
it is hard to analyse 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	
management 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	
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	

Table (4-9) Responses to the Question (Please describe any specific challenges faced in implementing or improving quality practices?)	
Responses	
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	

4.2.7 Responses for Part D – Potential AI applications in CQM practices

The Table (4-10) below presents the distribution of the study participants according to their perspective of Artificial Intelligence which were as follows:

Table (4-10) Distribution of the study subjects according to Artificial Intelligence				
Artificial Intelligence	Min-Max	Mean ± 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±0.75	4.00	83.71%
I personally use AI tools such as ChatGPT and similar, to improve my productivity	1-5	3.83±0.91	4.00	76.53%
I am familiar with AI technologies (e.g., ML, NLP, CV, IoT)	1-5	3.08±1.04	3.00	61.68%
There are initiatives in Our organization to integrate AI in project process including quality	1-5	3.18±0.97	3.00	63.61%
Special training on using AI tools is needed for our staff	1-5	4.05±0.96	4.00	80.96%
Staff are competent and open to using AI tools in quality management	1-5	3.35±0.90	3.00	67.03%
The current system in your organization is ready to be integrated with AI technology	1-5	3.30±0.88	3.00	66.02%
The integration of AI can positively influence the project's outcomes and overall success	1-5	3.80±0.87	4.00	75.90%

Table (4-10) Distribution of the study subjects according to Artificial Intelligence				
Artificial Intelligence	Min-Max	Mean $\pm$ SD	median	Mean score %
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 data that AI systems can use	1-5	3.55 $\pm$ 0.92	4.00	71.02%
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%

4.2.7a 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 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%).

4.2.7b 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 & data analysis (4.05, 81.08%), indicating effective use of AI tools to support operational & 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.

4.2.7c 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 related to AI scored a mean of 3.62 (72.34%).

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

Response to Question 27: Recommendation for developing & implementing AI solutions for CQM practices

Table (4-11): 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 avaliable 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
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 avaiabel, 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

Table (4-11): Responses to the Question (What recommendations would you give for developing and implementing AI solutions for CQM effectively?)

Responses
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

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

Table (4-12): 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

Table (4-12): Responses to the Question (Please share any observations, insights, thoughts or experiences where AI improved or could have improved project outcomes?)

Responses
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

4.2.10 Distribution of the study subjects according to Project Outcomes

Table (4-13): 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%

Table (4-13) presents distribution of study participants according to Project Outcomes

4.2.10a 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 means were tracking & reporting both direct and indirect quality costs (3.56, 71.14%), indicating a gap in documenting & measuring quality-related costs.

4.2.10b 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%).

4.2.10c 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%).
- Lowest mean was for minimizing post-handover claims (3.81, 76.14%), suggesting some issues may still need additional attention before final project delivery.

4.2.10d 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%).

4.2.11 Descriptive Statistics of Variables

Table (4-14) 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 (4-14) 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%, CQM 3.73±0.57 Mean score percent 74.55%.

Table (4-15) Descriptive Statistics of Moderating 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 (4-15) shows Descriptive Statistics of Moderating 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%, AI 3.67±0.46 Mean score percent 73.38%.

Table (4-16) 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 (4-16) 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%.

4.2.12 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 the study variables and making methodological decisions in research

4.2.12a - H1: There is a significant relationship between CQM, Project Outcomes, and Artificial Intelligence.

Table (4-17) Correlation Matrix between Variables - Independent Variables (CQM), Moderating Variables (AI) and Dependent Variables (Project Outcomes)															
Variables		Quality Planning	Quality Assurance	Quality Control	Quality Improvement	* 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											
* 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 shown in Table (4-17) presents the relationships between independent variables (Construction Quality Management – CQM), moderating variables (Artificial Intelligence – AI), and dependent variables (Project Outcomes). The analysis of the Pearson correlation coefficients (r) and their significance (p -values) provide insights into the strength & 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 moderating 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.

4.2.12b - H2: There is a positive impact of “CQM” on Artificial Intelligence.

Table (4-18) 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)											

To test the main study Hypothesis H2, the researcher used multiple linear regression analysis of the effect of “CQM” on Artificial Intelligence. The results of the simple regression analysis presented in the table indicate that 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 an improvement in CQM practices is associated with increased levels of artificial intelligence use, reflecting the enabling role of CQM practices in facilitating the effective adoption of AI technologies.

In summary, the findings indicate that enhancing CQM 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.

4.2.12c - Construction Quality Management “CQM” effect on AI

Table (4-19) 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 table (4-19) provide a comprehensive assessment of how the different dimensions of 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 (Sig = 0.065). This suggests that formalized assurance procedures—such as inspections, audits, and compliance protocols play 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 ($\beta = 0.217$, $t = 2.314$, 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 also 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.

4.2.12d - H3: There is a positive impact of CQM on Project Outcomes.

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

Table (4-20) 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 table (4-20) 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.

4.2.12e - Construction Quality Management “CQM” effect on Project Outcomes

Table (4-21) 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 Table (4-21) 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.

4.2.12f - Direct Effect of Artificial Intelligence on Project Outcomes

To examine the direct effect of Artificial Intelligence on Project Outcomes, the researcher used simple linear regression analysis of the effect of AI on Project Outcomes as shown below in Table (4-22).

Table (4-22) 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 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 positively influence various project outcomes.

4.2.12g - Direct Effect of Artificial Intelligence on Project Outcomes

Table (4-23) 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 in Table (4-23) above 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 readiness 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.

4.2.12h - H2: Moderation Test of Artificial Intelligence on the Relationship between CQM and Project Outcomes

Table (4-24) Testing the Moderation Role of AI on the relationship between CQM and project outcomes - 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).									

To test H2, the moderation effect of Artificial Intelligence on the relationship between CQM and Project and project outcomes, the regression results presented in the Table (4-24) examine the moderating effect of Artificial Intelligence (AI) on the relationship between Construction Quality Management (CQM) and Project Outcomes. A G*Power 3.1.9.7 analysis was conducted to assess the minimum required sample size, using a two-tailed correlation test, an assumed effect size of 0.30, $\alpha = 0.05$, and statistical power of 0.95, the required minimum sample size was estimated 138. Therefore, the final 167 responses exceeded the minimum requirement estimated by the power analysis.

The detailed Structural Equation Modeling (SEM) outputs, including the model diagrams, standardized and unstandardized estimates, model fit indices, and statistical power analysis, are provided in Appendix D. This appendix was included to support the interpretation of the moderation analysis and to ensure transparency in reporting the SEM results.

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 (CQM $\times$ 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.

4.3 Qualitative Data Analysis

The qualitative phase of this study aimed to complement quantitative survey analysis and results by examining operational records and governance documents related to CQM practices from JSWP. While the quantitative analysis identified statistical relationships between CQM practices, Artificial Intelligence and project outcomes, the qualitative analysis aimed to explore the operational context behind these relationships.

Specifically, the qualitative investigation aimed to understand how engineers, managers, and construction teams experience quality process in practice, how quality issues emerge and evolve during project execution, and how AI technologies may influence these processes in real world project environment.

Qualitative evidence was derived from multiple complementary sources including open-ended survey responses, historical quality records such as NCR & SOR logs, issue reports, program records including quality meetings, and client progress MOMs. The integration of these sources supports triangulation within the convergent mixed-method research design and provides contextual insights into organizational behavior, management discipline, and data readiness for AI integration within 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 167 valid responses included narrative comments in which participants described their experiences with CQM practices, highlighting operational challenges, and expressing their perceptions regarding the potential role of AI in CQM.

Second, operational project records within JSWP were examined. It includes quality management documentation such as NCRs, SORs, inspection logs, field reports, and audits findings. These records provide direct evidence of quality issues encountered during the project's execution, including types of defects, reoccurring quality issues, corrective action timelines, and recurring operational challenges.

Third, program governance documents were analyzed, particularly minutes of meetings from routine quality meetings, client progress meetings, and progress reports. These meetings serve as a key platform where contractors, consultants, and project management teams discuss recurring issues, site execution challenges, corrective actions, and overall program progress.

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 grouped into higher-order categories aligned with the theoretical constructs of Construction Quality Management, quality planning, control, assurance and improvement, with AI positioned as a moderator factor influencing these processes.

Next Pattern-matching logic was used from predefined list of quality issues derived from actual site insights, to test whether perceptions expressed in the survey were supported by evidence from logs and MOMs. This pattern matching enhances internal validity through data triangulation by comparing findings across independent qualitative data sources (Creswell & Plano Clark, 2022).

4.3.2 Document Corpus and Content Analysis Method

To complement the qualitative evidence obtained from survey responses and projects logs, a systematic content analysis of program governance documentation was conducted. The purpose of this analysis was to examine recurring management discussions within JSWP and identify operational patterns related to CQM practices.

The document corpus consisted primarily of MOMs records collected from the stormwater program repository. A total of 243 meetings documents were included in the analysis, covering the period between January 2021 and October 2025. The data set comprised two primary categories of governance records: quality assurance and control meeting minutes prepared by the supervision consultant, and client weekly progress meetings minutes documenting routine program coordination discussions. These meetings typically involve project managers, contractors, consultants, and client representatives, and serve as the primary forum for discussing program progress & schedule issues, operational challenges, coordination requirements, corrective actions, and operational challenges.

All available documents within this period were included in the analysis to ensure complete longitudinal coverage of the program lifecycle. As shown in table (4-25) the extracted textual corpus contained approximately 1.2 million characters of meetings discussion content, which were subsequently segmented into 11,090 individual statements suitable for thematic coding and analysis. A detailed explanation of the document extraction, preprocessing, and thematic coding procedures used in this analysis is presented in Appendix B.

Table (4-25) Summary of Document Sources and Coding Frequency for Qualitative Analysis

Document source	No. of Documents	Coded Statements	% of Total Statements
Client Progress Meeting Minutes (Arabic)	169	9,267	83.6 %
QAQC Meeting Minutes (English)	73	1,645	14.80 %
Survey Results (English)	1	178	1.6 %
Total	243	11,090	100 %

The results of this thematic analysis provide empirical evidence of the most frequently discussed quality management challenges within the program and serve as the basis for the operational themes presented in the following section.

4.3.3 Operational Themes Identified from MOM Analysis

Following the qualitative content analysis described in the previous section, the extracted statements from the meetings minutes were categorized into operational themes representing recurring quality management discussions within JSWP. The thematic coding process resulted in ten operational categories covering different aspects of CQM practices discussed during program governance meetings. Table (4-26) summarizes the major operational themes identified through the content analysis together with their relative frequency within the document corpus.

Table (4-26) Operational Quality Themes Identified in Program Meeting Records			
Operational Theme	Statement Frequency	Documents	Coverage (%)
Progress & Schedule Issues	3,176	201	83%
Poor Workmanship	1,565	231	95%
Contractor non-compliance	1,354	227	93%
Safety & Environmental Issues	1,330	195	80%
Inspection Failures	1,257	225	93%
Coordination Problems	1,207	207	85%
Delayed Corrective Actions	464	221	91%
Material Approval Delays	388	212	87%
Resource Constraints	218	166	68%
Management Escalation	130	132	54%

Source: Author's analysis of JSWP meeting minutes

As shown in the table, two complementary frequency indicators are reported. Statement frequency represents the total number of coded statements assigned to each theme across the document corpus, reflecting the intensity of discussion related to that issue. Document coverage represents the number of distinct meeting records in which the theme appears, indicating the breadth of the issue across the program.

Another important observation from the thematic frequency analysis presented in the table is the exceptionally high prevalence of several themes across the document corpus. Six of the ten identified themes appear in more than 80% of the analyzed documents. Such high levels of recurrence are uncommon in qualitative studies and indicate that the identified issues are not isolated project-specific problems but systemic program-wide challenges. This pattern reinforces the interpretation that quality risks within the program are driven by structural governance pressures rather than individual technical failures.

4.3.4 AI Risk and Escalation Model Findings

To complement the qualitative content analysis of meeting records, a risk and escalation model was developed to analyze the relationship between early warning indicators and subsequent quality issues within JSWP. The model utilizes structured issue records derived from project quality documentation, including NCRs and SORs, together with warning indicators extracted from program discussions and operational logs.

The dataset used for the model consists of 673 structured issue records and 113 warnings indicators associated with potential quality risks. Each warning type evaluated to determine whether it subsequently escalated into a formal NCR or SOR record. This allowed the analysis to quantify the probability that early governance warnings correspond to actual field level quality issues. Table (4-27) presents the escalation rates observed for the major warning categories identified in the dataset.

Table (4-27) Escalation Rates of Quality Warning Indicators	
Warning Category	Escalation Rate
Delayed-related warnings	66.70%
Material-related warnings	58.30%
Inspection-related warnings	48.40%

Overall, the results show that approximately 49.6% of warning signals escalated into formal NCR or SOR records, indicating a measurable relationship between governance level warnings and documented quality issues.

To operationalize the analytical framework developed in this research, the escalation model outputs and quality datasets were integrated into Quality Intelligence dashboard developed using Manus AI. The dashboard consolidates multiple quality performance indicators including escalation rates, contractor performance metrics, and issue closure trends. These indicators are visualized through an interactive interface designed to support program level monitoring of quality risks. Please refer to Appendix C for details on the complete development lifecycle of the JSWP Quality Intelligence Model, a thesis-grade analytical framework built to transform fragmented quality assurance logs into actionable intelligence for program management and academic research.

As shown in Figure (11) the dashboard provides an overall quality performance of the program through a composite Program Quality Index (QI). The index is calculated based on several contributing risk components including escalation penalties, overdue issue penalties, and high-risk warning indicators. Based on the analyzed dataset, the calculated program-level Quality Index was 45 out of 100, indicating that the program is considered “at Risk” quality performance category.



Figure (11) Quality Intelligence Dashboard Overview for JSWP Program
Source: Author-developed Quality Intelligence Dashboard based on JSWP quality datasets.

In addition to the composite QI, the dashboard summarizes key operational quality indicators including the total number of NCRs and SORs issued, the number of open and overdue issues, and the overall corrective action closure rate. At the time of analysis, the dataset included 249 NCR records, 421 SOR records, and 142 open quality issues, of which 141 were overdue, with an overall issue closure rate of 78.90%.

The dashboard also provides a comparative view of contractor-level quality performance through the Project Quality Index ranking, allowing project teams to identify variation in quality performance across different project zones and contractors.

4.3.5 Consolidated Analytical Themes

The operational findings obtained from the qualitative content analysis of meeting records, together with the results of the AI escalation model and dashboard indicators, were subsequently synthesized into four higher-level analytical themes. These themes represent key dimensions influencing the relationship between CQM practices and project outcomes withing JSWP.

Theme 1 – Predictive Quality Risk Detection

Respondents consistently highlighted the potential of AI to transform inspection from a reactive into proactive, predictive system. Phrases such as “AI could warn us before a defect happen”, “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 Microsoft Power BI, a simple text classification algorithm simulated using AI 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 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. The alignment between survey responses, NCR patterns, and MOM discussions indicates the presence of recurring quality risk patterns within projects.

Theme 2 – Data Governance & Digital Readiness

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 reporting 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 uncoded readable data. Which is also supported by responses highlighting the need to have enterprise platforms such as Aconex or Unifier instead of only relying on fragmented Excel files.

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 and 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 reflects the literature on AI readiness in construction such as Alhumoud et al., 2024.

Theme 3 – Organizational Discipline & Quality Governance

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 observation. The researcher developed quality monitoring 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 closure. 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.

Theme 4 – Human Capital & AI Adoption Readiness

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 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, stating that “AI cannot replace human judgment”, and organizational resistance. Many of these participants highlighted fears of “losing control”, “AI bias and reliability”, “dependence on unreliable technology, and “lack of clear system and training”.

This general 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 shift from manual representatives to data driven AI supported practices represents a core moderation channel of AI between CQM and project outcomes.

Together, these four themes provide qualitative evidence regarding the operational, technical, and organizational factors influencing the integration of AI within CQM practices. The themes complement the quantitative findings presented earlier in this chapter and provide contextual insights into how AI capabilities interact with existing quality management processes within large infrastructure programs.

4.4 Summary of Results

This chapter presented the empirical findings of the study through the integration of quantitative and qualitative analysis examining the relationship between Construction Quality Management, Artificial Intelligence, and project outcomes within JSWP.

4.4.1 Summary of Hypotheses Results

The findings supported Hypothesis H1 by showing that the size and complexity of JSWP placed considerable pressure on traditional CQM practices. Although CQM remained essential, the project evidence showed many reoccurring quality issues, coordination challenges, materials related issues, delays in corrective actions, and fragmented quality data, indicating that current quality approach alone at JSWP were insufficient in such complex infrastructure environment.

Hypothesis H2 was not statistically significant and supported in terms of AI's moderating effect. The interaction between CQM and AI didn't significantly strengthen the relationship between CQM and project outcomes. However, the findings showed that AI still provides practical value as an operational enhancer, particularly in monitoring, data analysis, pattern identification, and decision support.

Hypothesis H3 was supported by the qualitative and practical findings, showing barriers including financial, organizational, technical, ethical barriers, and current quality tools such as excel and the absence of QMS platform. These barriers limit effective AI integration into CQM and therefore explain why AI did not appear as a strong moderator in the tested model.

4.4.2 Summary of Findings

The quantitative analysis, based on the survey responses from project professionals, provided statistical evidence regarding the relationship between CQM practices and project performance indicators including cost, schedule, quality and stakeholder satisfaction. The results indicate that effective implementation of CQM practices is positive associated with improved project outcomes. The statistical analysis also explored the moderating role of AI technologies in strengthening this relationship.

The qualitative analysis complemented these findings by examining operational project records and governance documentation. Content analysis of program meeting minutes revealed recurring operational themes related to contractor non-compliance, workmanship quality, inspection failures, coordination challenges, and delays in corrective actions. These themes highlight common quality management challenges encountered during the implementation of large infrastructure programs.

To further examine the relationship between early warnings indicators and documented quality issues, a risk and escalation model was developed using structured NCR and SOR record together with warning indicators extracted from project discussions. The analysis showed that a significant proportion of warning signals escalated into formal quality issues, demonstrating a measurable relationship between governance-level and field-level quality events.

The analytical framework was further operationalized through the development of a Quality Intelligence dashboard integrating issue records, escalation indicators, and contractor performance metrics. The dashboard provided program level visibility of quality performance indicators including issue closure rates, escalation penalties, and the composite Program Quality Index.

Finally, the qualitative findings were synthesized into four analytical themes reflecting key dimensions influencing the integration of AI within CQM practices: predictive quality risk detection, data governance and digital readiness, organizational discipline and quality governance, and human capital readiness for adoption of AI.

Together, the results presented in this chapter provide a comprehensive view of the operational, technological, and organizational factors influencing the implementation of AI-supported CQM practices within JSWP. These findings form the basis for the interpretation and discussion of research implications presented in the following chapter.

CHAPTER FIVE

RESEARCH CONCLUSION & RECOMMENDATION

5.1 Introduction

This chapter presents a comprehensive synthesis and critical discussions for the research findings that was reported in Chapter 4. The chapter highlights and links empirical results to the research objectives, theoretical foundations, and the research gap. The primary purpose of this research study was to examine the impact of Construction Quality Management (CQM) practices on Construction Project Outcomes and explore the moderating role of AI within this relationship.

The statistical analysis for the survey results revealed three main findings, First, CQM Practices demonstrated a statistically significant positive effect on project outcomes, confirming the importance of quality planning, quality assurance and control, and quality improvement in supporting cost, schedule, quality and customer satisfaction. Second, Artificial Intelligence exhibited a statistically significant direct effect on project outcomes, indicating that AI-related awareness, readiness, utilization, and implementation capabilities can contribute positively to project performance. Third, the SEM moderation analysis showed that the interaction effect between CQM and AI was not statistically significant. Therefore, AI was not statistically supported as a moderator of the relationship between CQM and project outcomes in the tested model. This finding suggests that AI currently functions as an operational enhancer, not as fully integrated structural moderator within quality governance systems.

5.2 Critical Synthesis of Empirical Findings

The results in chapter four showed the statistical analysis of the relationship between CQM, Artificial Intelligence, and Project Outcomes. The results confirmed the existence and structure of the relationship between the variables, but statistical significance alone does not fully explain the structural dynamics underlying the performance improvement in mega construction environments.

The discussion in this chapter is aligned with the hypothesis structure of the study. The first hypothesis “H1” addressed in JSWP how the size and complexity of the program place pressure on current CQM practices. The second one “H2” examined whether AI-Driven CQM practices can moderate the relationship between CQM and project outcomes, while H3 explained the barriers on JSWP that limited the effective integration of AI into current CQM practices, because of the absence of a sufficient QMS platform, awareness and skill of using trending AI technology and lack of management initiatives. This structure allowed the findings to be interpreted as a connected research argument rather than as separate statistical results.

Accordingly, this chapter provides important synthesis of the empirical findings by drawing on the complementary strengths of the mixed-method research approach that is used in this study. Quantitative evidence derived from descriptive statistics and structural equations modeling is integrated with the qualitative insights obtained from the survey responses. This mix of both methods allowed for a richer and more nuanced interpretation of the governance implications of the results. It also forms a triangulation of quantitative and qualitative evidence, enhances the robustness of the analysis and also strengthens the validity of conclusions derived from the study.

The discussion will not only be restating numerical outcomes, but it will also examine how CQM and AI operate within project governance structures, whether their influence reflects structural integration or parallel contribution. Also, what the findings imply regarding digital maturity in large scale infrastructure programs, such as JSWP.

5.2.1 Triangulation of Results

To further examine the convergence between the quantitative statistical findings and the qualitative thematic analysis, a triangulation matrix was developed following the joint-display approach recommended in mixed-methods research (Creswell & Plano Clark, 2018). As shown in Table (5-1) the matrix integrates qualitative themes extracted from the survey analysis, with the analysis of 243 meeting minutes and the quantitative findings produced by the AI escalation model and issue dataset. This approach enables a direct comparison between governance discussions, operational quality events, and statistical escalation patterns, thereby strengthening the construct validity of the study.

Table (5-1) Convergent Mixed-Methods Triangulation Matrix Integrating Survey Results, Governance Records, and AI Escalation Modeling

Qualitative Theme	Survey Evidence	Qualitative Evidence (MOM)	Quantitative Finding	AI Analytical Output	Escalation Rate	Convergence
Progress & Schedule Issues	Respondents identify schedule pressure as a major quality risk	3,176 statements (83% of documents)	Delay warnings dominate	AI identifies delay warnings as highest-risk signal	66.70%	Strong
Poor Workmanship	Survey respondents highlight recurring workmanship defects	1,565 statements (95%)	NCR clusters in workmanship defects	AI clusters general quality risk patterns	47.70%	Strong
Contractor non-compliance	Survey indicates contractor compliance as major quality factor	1,354 statements (93%)	Contractor risk dominant predictor	AI contractor risk index identifies high-risk contractors	33-72%	Strong
Inspection Failures	Survey highlights inspection gaps and monitoring challenges	1,257 statements (93%)	Inspection failures escalate quickly	AI predicts escalation windows	49%	Strong
Coordination Problems	Survey identifies coordination barriers in complex projects	1,207 statements (85%)	Lower escalation frequency	AI flags coordination issues as operational risk	33.3%	Strong

The triangulation results demonstrate strong convergence between the three data sources. Survey responses highlighted several key quality concerns, including schedule pressure, contractor non-compliance, and workmanship issues. These perceptions align closely with the themes most frequently discussed in program governance meetings. For instance, the qualitative theme *Progress and Schedule Issues*, which appeared in 3,176 coded statements across 83% of the analyzed documents, corresponds directly with the quantitative finding that delay warnings exhibit highest escalation probability (66.7%). Similarly, *Poor Workmanship*, appeared in 95% of the documents, aligns with the widespread occurrence of general quality-related NCRs within the structured issue dataset. The AI escalation model further confirms these patterns by quantifying the probability that early governance warnings escalate into formal quality events.

This convergence between perception-based survey data, operational governance discussions, and quantitative escalation analysis provides strong evidence supporting the study's interpretation of quality risk dynamics in large infrastructure programs. The combined findings indicate many quality risks are visible within project governance discussions before they formally appear as NCRs or SORs, or other non-conformance events. In this context, AI does not replace existing QMSs, rather, it transforms dispersed operational and governance signals into measurable quality intelligence that can support earlier intervention, strengthen risk visibility, and improve data-driven decision-making.

5.2.2 Operational Evidence from Program Governance Records

In addition to the statistical findings presented in Chapter Four, qualitative evidence obtained from program governance records provides further insight into how quality management challenges emerge during project implementation. A longitudinal thematic analysis of project governance documentation was conducted using 243 meeting records, including 73 QA/QC coordination meetings and 169 client progress meetings (2021 to 2025). The analysis produced more than 11,000 coded statements related to quality management practices, offering a detailed view of operational issues discussed throughout the program lifecycle.

The results revealed recurring operational themes including contractor non-compliance, poor workmanship, inspection failures, schedule pressure, coordination challenges, and delayed corrective actions. As illustrated in Table (5-2), several operational quality risks appeared repeatedly in program governance discussions across multiple meetings and project zones, indicating that quality challenges were not isolated project level incidents but recurring operational patterns within the program. These recurring issues provide important contextual evidence explaining why certain warning signals later escalated into formal quality events identified in the analytical models presented in Chapter Four.

Table (5-2) Recurring Quality Issues Identified in Program Governance Meetings		
Operational Theme	Frequency of Discussion	Documents Coverage
Poor Workmanship	High	Appeared in majority of meetings
Contractor non-compliance	High	Appeared in most project reviews
Inspection Failures	High	Repeatedly discussed in QA/QC meetings
Schedule Pressure	High	Frequently linked to quality concerns
Delayed Corrective Actions	Moderate	Repeated across multiple projects
Source: Inspired by Creswell and Plano Clark (2017, p. 119)		

The longitudinal nature of these records provides important context evidence supporting the quantitative findings. Many of the quality risks identified through analytical models were already visible in governance discussions before escalating into formal NCR or SOR. This observation highlighted the role of governance discussions as an early signal source for quality risks within complex infrastructure projects.

Also, the analysis indicates that the program's quality management processes were effective at identifying and documenting issues through inspections, NCRs, and meeting discussions. However, the persistence of similar issues across multiple years suggests that these mechanisms functioned primarily as escalation tracking tools rather than preventive control systems. Corrective actions were frequently discussed but their frequency was moderate compared to other operational themes. This is why quality issues often remained open across successive meetings, indicating limitations in the system's ability to eliminate root causes, and apply proper preventive measures. It also indicates that existing problems are not being closed effectively and reflects the large number of overdue issues 141 out of 142 open issues.

5.2.3 CQM as Structural Governance Backbone

The empirical findings from the study confirm that CQM constitutes the primary governance driver influencing Project Outcomes. The overall CQM mean score (3.73) reflects a moderately high level of institutional quality practices across the sampled projects. More importantly, the SEM demonstrated a strong and statistically significant direct effect of CQM on Project Outcomes ($\beta = 0.451$, $p < 0.001$). This result confirms that structured quality planning, quality assurance & control, and quality improvement mechanisms remain central to performance delivery.

The descriptive results indicate that quality culture and top management support recorded the highest means (above 4.10), which suggests that quality is formally recognized as a core organizational value. Quality control mechanisms also demonstrated relatively strong implementation, particularly in inspection processes and documentation systems. These findings collectively suggest that procedural and structural components of governance are firmly embedded in the projects examined.

However, the results simultaneously revealed operational imbalances within the quality system. CAPA implementation scored the lowest mean (3.17), which indicates weakness in feedback loops effectiveness, it also reflects reoccurring issues highlighted in JSWP quality logs. Furthermore, while spreadsheets tools showed the highest utilization (mean = 2.64) within the survey results, enterprise-level integrated software adoption showed a low mean of (2.64). Using traditional spreadsheets means a reliance on fragmented tracking systems rather than integrated digital governance platforms.

The structural configuration within the projects reflects what may be described as procedural maturity without a digital integration maturity. CQM operates as a compliance-driven governance framework, but its analytical capacity remains constrained by the limited system integration and data automation. Consequently, as CQM significantly explains performance variance its influence is primarily rooted in structured discipline rather than predictive intelligence, that can support CAPA and reduce the reoccurrence of quality issues.

From a governance perspective, these findings position CQM as the foundational backbone of project control. It establishes accountability, standardization, and risk mitigation measures. However, the limitations found in digital infrastructure suggest that quality governance within JSWP projects remains largely reactive rather than fully data driven and proactive. This finding highlights a gap between current operational practices and the preventive orientation emphasized by classical quality theorists, such as Deming, Juran, and Crosby, whose frameworks advocate systematic planning, early detection of quality issues, and continuous improvement as a fundamental principle of effective quality management.

5.2.4 AI as an Emerging Performance Enabler

5.2.4.1 Empirical Evidence of AI Performance Contribution

Artificial intelligence demonstrated a statistically significant direct effect on Project Outcomes within the SEM model ($\beta = 0.230$, $p = 0.001$), confirming AI adoption contributes independently to project performance. The overall AI mean score (3.67) indicates moderate organizational engagement with AI-related practices. Notably, interest in learning and using AI tools recorded high values from the survey results (mean=4.19). Respondents expressed strong belief in AI's potential to enhance operational efficiency and data analysis.

Despite this positive orientation, the readiness indicators present a more complex picture. The system readiness within sample projects for AI integration recorded a low to moderate mean (3.30), and enterprise software adoption remained low across projects. Additionally, qualitative responses highlighted recurring themes of management resistance, especially in older generations, as well as cost concerns, limited infrastructure, and inadequate training.

5.2.4.2 Organizational Readiness and Digital Maturity

The descriptive results further indicate that AI utilization is currently concentrated for analytical and supportive tasks, such as data visualization, automation and document generation, rather than being embedded within core quality workflows. This level of utilization of AI technology implies that AI functions as an augmentation tool rather than a structurally integrated governance mechanism.

The coexistence of high interest and moderate infrastructure readiness reflects what may be characterized as transitional digital maturity stage. Organizations recognize the potential of AI but have not yet invested in adopting this promising technology, nor supported adoption of AI within their quality management systems. As a result, AI might improve performance directly through efficiency gains and enhanced analysis, but it does not fundamentally alter the structural dynamics of quality governance.

The interpretation is reinforced by qualitative evidence emphasizing reliance on spreadsheets, fragmented project data, and limited cross system integration between departments. Without unified digital architecture, AI applications remain promising rather than transformative and will not provide the desired cross departmental benefits and most importantly improving projects predictability and decision making.

5.2.4.3 Escalation Mechanism and Predictive Quality Intelligence

The qualitative evidence also reveals an important operational mechanism linking governance discussions to field-level quality outcomes. As discussed in early sections on the analysis of the 243 program governance documents, the results showing several repeated quality issues including contractor non-compliance, poor workmanship, inspection failures, and schedule pressure. These recurring issues were repeatedly discussed across a large number of project meetings, throughout the years, indicating that quality risks were already visible during meetings discussions long before they escalated into formal NCR or SOR.

The AI escalation model developed as part of the Quality Intelligent Dashboard provides a quantitative representation of this phenomenon. By linking 113 governance warning indicators with 673 structured quality issue records, the model demonstrates that substantial proportion of early warning subsequently escalate into documented

quality events. In particular, delay- related warnings showed the highest escalation probability, highlighting the critical role of schedule pressure as a driver of quality failures. This observation is consistent with the qualitative thematic analysis of governance records, where schedule pressure appeared as the most frequently discussed issue across project meetings.

These findings suggest that meetings discussions functions as an early signal system for emerging quality risks. When projects experience schedule pressure, contractors may bypass inspections procedures, or delay corrective actions or proceed with unapproved materials, or unapproved MOS, which increase the likelihood of quality escalation events. AI-Based analytical models therefore enable the transformation of these dispersed governance signals into measurable risk indicators capable of supporting proactive quality management decisions.

5.2.4.4 Quality Intelligence Dashboard Interpretation

The findings suggest that quality governance in large infrastructure program operates across three distinct decision layers: technical quality control, operational project delivery, and strategic program oversight. While each layer addresses different aspects of project performance, the absence of an integrated analytical framework limits the ability of decision-makers to identify systemic risk patterns. The proposed Quality Intelligence Dashboard addresses this limitation by integrating data across governance layers, enabling earlier detection of quality risks and more proactive program-level decision-making.

In addition to that, the analytical insights derived from the escalation model into practical decision-support capabilities, the developed Quality Intelligence Dashboard integrates structured issue records, escalation indicators, and contractor performance metrics. The dashboard consolidates quality data across multiple projects and visualizes key performance indicators including escalation behavior, overdue corrective actions, contractor risk rankings, and composite Quality Index.

The resulting program-level quality score indicates that JSWP currently operates within “At Risk” quality performance category, reflecting the cumulative effect of recurring operational issues identified throughout the analysis. The dashboard therefore functions as a governance tool that transforms fragmented dispersed project data into a unified operational picture of program quality performance. By visualizing escalation patterns, contractor performance variation, and issue closure behavior, the system provides management teams with earlier visibility of emerging quality risks and supports more proactive intervention strategies.

Together, the escalation model and the Quality Intelligence Dashboard demonstrate how megaproject governance can evolve using AI-enabled intelligence systems, and how it can transform governance signals and operational project data into predictive quality intelligence capable of supporting proactive quality management systems.

5.2.5 Structural Interpretation of SEM Model and Moderation Analysis

5.2.5.1 Purpose of the SEM Model Analysis

The structural Equation Modeling (SEM) analysis provided a more rigorous interpretation of the relationship Among Construction Quality Management, Artificial Intelligence, the interaction term between CQM and AI, and Project Outcomes. Unlike simple regression, SEM allows the study to assess the structural relationship among latent constructs while accounting for the measurement structure of CQM, AI, and project Outcomes. The detailed SEM outputs supporting this interpretation are provided in Appendix D, including the model estimates, fit indices, and statistical power analysis.

5.2.5.2 Direct effects of CQM and AI on Project Outcomes

The SEM results confirmed that CQM has statistically significant positive effect on Project Outcomes, with an estimate of $\beta = 0.4451$, a critical ratio of 6.375, and a significance level of $p < 0.001$. This supports the view that stronger CQM practices contribute to improved cost performance, schedule performance, overall project quality, and customer satisfaction. The results also showed that AI has a statistically significant direct effect on Project outcomes, with an estimate of $\beta = 0.230$, a critical ratio of 3.289, and a significance level of $p = 0.001$. This indicates that AI-related practices, including awareness, readiness, utilization, and the ability to address AI implementation challenges, can contribute positively to project performance.

5.2.5.3 Moderation Effect of AI

However, the interaction effect between CQM and AI was not statistically significant. The SEM estimate for the interaction term was $\beta = 0.017$, with a critical ratio of 0.759, and $p = 0.448$. This indicates that AI didn't significantly moderate the relationship between CQM and Project Outcomes in the tested model. In other words, while both CQM and AI independently contributed to better project outcomes, AI didn't significantly strengthen or change the effect of CQM on project outcomes within the current study context.

In other words, while both CQM and AI independently contributed for better project outcomes, AI did not significantly moderate (i.e. strengthen or chang) the effect of CQM on Project Outcomes within the current study context of JSWP. Therefore, the result should not be interpreted as evidence that AI has no value in construction quality management. Rather, it suggests that AI is currently functioning more as an operational enhancement, than as a fully integrated structural moderator. In the context of Jeddah Stormwater program, the limited moderation effects can be explained by the early maturity of AI adoption, reliance on fragmented data sources and spreadsheets-based tracking. Also, the absence of quality / or digital platforms and therefore absence of governed AI-enabled quality management system.

5.2.5.4 Model Fit Indices

The SEM model fit indices support the acceptability of the model. The CMIN/DF value of 2.496 falls within the acceptable range, while the CFI value of 0.904 indicates acceptable model fit. The GFI value of 0.894 and AGFI value of 0.839 are close to commonly accepted thresholds. The RMSEA value of 0.095 suggests moderate fit and indicates that the model could be improved in future studies through larger samples, additional constructs, or more mature AI integration measures.

5.2.5.5 Explaining the Difference Between Regression and SEM Results

It is important to note that earlier, the hierarchical regression analysis suggested a statistically significant interaction effect. The divergence between the regression-based moderation result and the SEM outcome warrants methodological clarification. Hierarchical regression relies on observed composite variables and does not explicitly

account for measurement error. In contrast, SEM models are latent constructs, incorporates measurement reliability, and simultaneously estimates structural paths within an integrated framework. As a result, SEM provides a more conservative and statistically rigorous assessment of interaction effects in latent variable research. The absence of significant interaction path in the SEM model therefore represents the more robust structural conclusion. Therefore, the absence of a significant interaction path in the SEM model represents the more robust structural conclusion of this study

5.2.5.6 Interpretation in the JSWP Context

The descriptive and qualitative findings further support this interpretation. Respondents reported high awareness of AI capabilities and strong belief in its potential impact and their willingness to discover it in depth. But, organizational digital readiness or maturity indicators, such as enterprise system integration and infrastructure adequacy, were comparatively moderate to low. Moreover, qualitative responses highlighted management resistance, low interest in investments in new technologies, reliance on traditional tools, lack of enterprise platforms, and limited structural digital integration. These conditions suggest that AI adoption within the examined projects on JSWP remains at an augmentation stage rather than a transformational integration stage.

5.2.5.7 Governance Implications

From a governance perspective, a significant moderation effect would imply deep structural interdependence between quality management systems and digital intelligence mechanisms. The absence of statistically significant interaction effect in the SEM model indicates that such structural integration has not yet been fully realized in the projects due to the current capabilities of CQM practices as explained earlier.

Instead, AI currently contributes through parallel and partially independent influence, often driven by individual team members or as standalone initiatives, rather than organizational-wide system embedded quality governance. This pattern has been reported in several projects within JSWP, and it reflects evolutionary stage of digital maturity in which technological or AI-enhanced CQM practices tools can support overall quality performance independently before becoming fully integrated within governance architecture of CQM.

These discovered patterns provide a subtle understanding of AI adoption in large infrastructure programs and support the broader conclusion of this study: CQM remains the foundation of project performance, while AI currently acts as an operational enhancement. For AI to become a true structural moderator, organizations need integrated data platforms, stronger governance, management support, improved data quality, and mature digital quality systems.

5.3 Theoretical Contributions and Advancement of Knowledge

This study contributes to the advancement of knowledge related to the intersection of Construction Quality Management, Artificial Intelligence, and project performance of mega-projects and large-scale infrastructure programs. While prior research has examined quality management frameworks and, separately, the application of AI technologies in construction, limited empirical work has investigated their integrated structural relationships within a unified analytical model. Building upon the theoretical foundations discussed in Chapter Two, namely Total Quality Management (TQM), ISO 9001, and the foundational philosophies of Deming, Juran, and Crosby. This study extends quality theory into a digitally augmented governance context. The findings not only validate core CQM principles but also provide empirical insight into the evolving maturity stage between traditional quality systems and emerging Quality 4.0 paradigms.

5.3.1 Contribution to Construction Quality Management Theory

The first theoretical contribution of this study lies in reinforcing and empirically validating CQM as a systematic governance construct rather than a collection of isolated procedural activities, that satisfies the compliance requirements. By modeling CQM as a latent variable composed of quality planning, assurance, control and improvement, the study confirms that quality management operates as an integrated governance architecture influencing overall project performance. The significant positive relationship observed between CQM, and project outcomes further supports the view that structured QMS remains a key determinant of project performance, thereby reinforcing the theoretical assumptions established by classical quality management scholars.

Deming's PDCA cycle emphasized continuous process control and systematic improvement. Juran's quality trilogy structured quality into planning, control and improvement mechanisms. Crosby's Zero Defects philosophy advocated prevention over correction. These foundational theories collectively shaped modern quality systems, particularly ISO 9001 and TQM, as discussed in chapter two. Therefore, the empirical validation of CQM in this study confirms the following:

- Quality Planning, Control, Assurance, and Improvement operate as an integrated governance system.
- Structured quality systems remain essential in managing complexity of large-scale programs such as JSWP.
- Proactive and preventive approaches continue to influence cost, schedule, quality, and stakeholder satisfaction.

Thus, this research reinforces the enduring theoretical relevance of classical quality philosophies within contemporary mega-projects settings.

5.3.2 From TQM to Quality 4.0: Empirical Insights

The findings suggest that quality failures in megaprojects are closely linked to governance-driven schedule pressure rather than isolated technical defects. While traditional quality management systems focus on detecting defects during construction, the integration of AI-enabled analytical tools can enhance governance by identifying systemic risk patterns across operational datasets. This shift from reactive defect management to predictive risk intelligence represents a key contribution to the proposed Quality Intelligence Model (QIM).

The findings suggest that the sampled projects operate within a transitional stage of digital maturity. Classical frameworks such as TQM emphasize organizational culture, leadership commitment, and system wide responsibility. International standards such as ISO 9001 formalized these principles into documented processes, standardized procedures, and auditable management systems. However, the emergence of Industry 4.0 technologies introduces new capabilities that extend beyond procedural compliance. Technologies such as AI, predictive analytics, and digital monitoring systems enable organizations to detect patterns in operational data, anticipate risks, and

support real-time decision making. But this transition toward industry 4.0 requires strong foundational governance system, as the empirical results indicate the following:

- Strong direct effect of CQM on outcomes (confirming traditional frameworks).
- Significant direct effect of AI in project performance.
- Limited moderation effect in SEM.

The empirical result of this study reflects this evolving relationship between traditional quality management and emerging digital technologies. The quantitative findings demonstrated a strong direct effect of CQM practices on project outcomes, confirming the continued relevance of established quality management frameworks. At the same time, artificial intelligence showed a statistically significant direct contribution to project performance, indicating that digital technologies can independently enhance project delivery processes. However, the moderating effect of AI within the structural equation remained limited.

This pattern suggests that AI currently functions primarily as an enhancer rather than as a fully embedded systemic moderator within construction quality governance. The findings therefore align with the emerging Quality 4.0 discourse, which conceptualize digital technologies as integrated quality enablers that extend traditional management systems rather than replacing them.

The qualitative findings further support this interpretation. Recurring governance discussions regarding schedule pressure, contractor non-compliance, and workmanship deficiencies reveal that many quality risks remain rooted in operational and organizational factors rather than technological limitations. The escalation analysis conducted in this research demonstrates that these governance signals can be transformed into measurable risk indicators through AI-supported analytical models. When combined with dashboard-based monitoring systems, these models provide managers with earlier visibility of emerging quality risks. However, the incomplete moderation observed in this study indicates that full quality 4.0 integration has not yet matured within examined context. Accordingly, this research positions large-scale infrastructure programs within a transitional evolution from procedural TQM based systems toward digitally augmented quality governance.

These observations highlight the need for structured frameworks capable of integrating traditional quality governance with emerging digital analytical capabilities. In response, this research proposes future research for the Quality Intelligence Model (QIM) as a conceptual framework for integrating artificial intelligence into CQM systems. This recommendation is consistent with Soney et al. (2020), who emphasized that effective Quality 4.0 implementation requires leadership, training, organizational culture, top management support, data integration and advanced analytics.

5.3.3 Contribution to Artificial Intelligence Research in CQM

The second contribution addresses a critical gap in AI research within construction management. Existing studies frequently examine AI applications in specific defined technical domains, such as defect detection, computer vision monitoring, smart sensors, or drone inspections. While these studies demonstrate the technological capabilities of AI applications, they rarely position and discuss artificial intelligence within the broader governance structure of quality management systems. Although AI technologies have shown the potential to enhance CQM practices, their impact may remain below the desired level when implemented in the absence of robust quality governance frameworks capable of guiding their strategic integration.

This study adds in this regard by modelling AI as a system level construct within a structured equation framework, by examining its relationship with CQM and overall Project Outcomes. The findings confirm that AI exerts a statistically significant direct effect on project performance ($\beta = 0.230$, $p = 0.001$), thereby extending AI research beyond isolated technical applications to performance-level influence.

However, the absence of significant moderating effect in the SEM model results suggests that AI adoption within the examined context remains additive rather than structurally transformative. This distinction advances AI scholarship by differentiating between technological augmentation and systematic governance integration. It indicates that AI may enhance efficiency and analytical capacity without yet restructuring the underlying quality governance architecture.

5.3.4 Contribution to Moderation and Digital Integration Literature

Another important methodological perspective is the theoretical contribution in the empirical examination of AI as a moderating variable within construction quality governance. While hierarchical regression analysis suggested potential interaction tendencies between AI and CQM, the Structural Equation Modeling (SEM) analysis did not confirm a statistically significant moderating effect once latent constructs and measurement error were accounted for.

This methodological clarification is considered a contribution as it demonstrates the importance of using structural modeling techniques when testing moderation in complex governance systems. The divergence between regression and SEM findings underscores the necessity of cautious interpretation in digital transformation research. More importantly, the results also show that AI and CQM currently operate in parallel rather than as structured interdependent systems. Moderation implies deep integration, feedback loops, and embedded predictive governance mechanisms. The absence of a significant interaction effect indicates that such integration has not yet been fully realized within JSWP projects.

The finding contributes to digital literature by suggesting that transformation may occur in stages, rather than structural shift. AI adoption may initially function as an independent performance enhancer before evolving toward deeper and foundational integration within governance systems. Accordingly, digital integration in Construction Quality Management may be conceptualized as a staged process consisting of Stage 0 – Traditional CQM, Stage 1 – AI-enhanced CQM, and Stage 2 – Integrated digital governance, where AI becomes structurally embedded within quality management processes. Empirical evidence suggests that the examined projects are positioned near the AI-enhanced augmentation stage, transitioning between Stage 0 and early Stage 1.

5.3.5 Contribution to Mega-project Governance in the Saudi Context

The fourth contribution relates to the contextual regional scholars. Mega infrastructure projects present governance challenges distinct from smaller construction environments due to scale, stakeholder complexity, regulatory oversights, and financial magnitude. Despite increasing global attention on digital transformation in construction, empirical

evidence from large-scale projects in the Saudi context remains limited. This study provides statistically validated insights derived from high budget, multi stakeholder infrastructure program. By examining the interplay between quality governance and digital adoption in this context, the research contributes regionally grounded empirical evidence to the broader literature on construction digitalization.

Furthermore, the findings also reveal that while quality governance structures are relatively mature within these projects, digital integration remains transitional. This nuanced understanding contributes to policy and governance discussions within rapidly developing infrastructure ecosystems, offering academically grounded evidence rather than technology driven optimism.

5.3.6 Concluding synthesis of theoretical contributions

Overall, the research findings highlight that while classical Construction Quality Management frameworks continue to provide the structural foundation for quality governance, the integration of Artificial Intelligence remains at an evolving stage. This observation underscores the need for further research into governance models capable of systematically embedding digital intelligence within quality management systems.

5.4 Practical Implications and Evidence-Based Recommendations

The empirical findings of this study provide important practical implications for governance and management practices within large-scale construction programs. The results confirmed that CQM remains the dominant structural driver of project performance, while AI contributes independently as emerging performance enhancer. However, the absence of statistically significant moderating effect indicates that AI technologies are not yet structurally embedded within quality governance mechanisms. The survey results and qualitative responses further revealed organizational challenges including limited digital infrastructure integration, reliance on spreadsheet-based tracking tools, and gaps in infrastructure and AI readiness and training for integration.

Based on these insightful findings, the recommendations of this study are proposed to strengthen governance maturity and enable more effective integration of digital intelligence within the QMS. Since AI was found to contribute directly to project outcomes but was not statistically supported as a structural moderator in the SEM model, the recommendations focus on the digital, organizational, and governance

conditions required to move from traditional CQM toward AI-enhanced CQM and, eventually, integrated digital quality governance. This direction is consistent with Sony et al. (2020), who emphasized that effective Quality 4.0 implementation requires not only digital technologies, but also big data handling, advanced analytics, integration, leadership, training, organizational culture, and top management support. Table (5-3) summarizes implementation action plan derived from the empirical findings of this study translating the proposed recommendations into structured governance & operational initiatives.

5.4.1 Establish Executive-Level Digital Quality Governance

The survey finding confirms that leadership commitments and quality culture were among the strongest dimensions of CQM. At the same time, qualitative responses show organizational hesitation toward digital transformation as well as AI integration and adoption within current systems. This is suggesting that while current quality governance structure is strong, digital integration has not yet been strategically established. Senior leaders should therefore establish executive-level digital quality governance mechanisms that formally integrate AI-supported technology into project management frameworks, including CQM, and decision-making processes. Such type of initiative will support the governance and ensure that digital transformation initiatives align with existing quality management frameworks rather than operating as isolated technological enhancers.

5.4.2 Integrate AI Analytics within Quality Monitoring Systems

The SEM results demonstrated that there is a statistically significant direct effect of AI on project outcomes, indicating that digital tools can enhance project performance through improved information processing and analytical capabilities. However, the absence of moderating effect suggests that AI tools are not yet fully embedded within the current quality governance systems. Therefore, organizations should seek to integrate AI supported analytical power into quality monitoring platforms, enabling automated analysis of inspection results, defect patterns, and performance indicators. This integration would strengthen the analytical capacity of the QMS and support more proactive decision making by management.

5.4.3 Reduce Reliance on Spreadsheet-Based Quality Tracking

Survey findings also revealed extensive reliance on spreadsheets for tracking quality-related information, while enterprise-level digital platforms such as Aconex were rarely used. Although spreadsheets offer operational flexibility, limit system integration and reduce the effectiveness of data-driven platforms that unify and organize the forms and copies of used practices. Organization should transition toward integrated digital platforms that centralize inspection logs, non-conformance reports, and quality performance metrics within unified databases. Such systems would enable real-time monitoring and improve transparency across project teams.

5.4.4 Strengthening Data-Driven Corrective and Preventive Processes

The descriptive results indicate that comparatively lower scores for corrective and preventive action (CAPA) processes compared with other CQM dimensions. It suggests that issues are detected through inspections, and systematic learning from recurring quality issues is not established. Construction organizations, especially contractors, should strengthen CAPA process through digital root-cause analysis tools that are capable of identifying and flagging recurring defect patterns and linking them to preventive strategies. Enhancing analytical feedback loops will support a shift from reactive correction of issues toward predictive quality management.

5.4.5 Develop AI Competencies Among Project Professionals

Survey responses showed strong interest among participants, especially younger generations, in learning AI tools but limited level of infrastructure readiness and formal training. This gap indicates that technology adoption must be supported by professional training and capability development. Organizations should therefore introduce structured training programs that equip quality and project teams and project managers with skills in data analytics, AI-supported reporting tools, and digital site inspection systems. At the same time, organizations must strengthen awareness of cybersecurity, data privacy, and data governance frameworks. The increasing use of AI-driven systems requires responsible management of project data, protection of digital infrastructure, and clear governance policies for data access and usage. Developing these competencies will enable quality professionals to effectively and securely utilize emerging digital technologies within their daily workflows.

5.4.6 Establish Standardized Data Architecture & Governance for Integrated Project Data

Fragmented data structures and inconsistent data gathering and reporting formats, especially using spreadsheets, were identified from responses as barriers to digital integration. Without standardized data architecture, the effectiveness of AI-supported analytics remains limited. Beyond improving quality reporting, a standardized data structure enables the integration of information across multiple projects disciplines, allowing organizations to combine data related to quality, safety, schedule, and cost.

This cross-disciplinary integration strengthens the analytical power of digital systems by enabling the identification of relationships between site delays, safety incidents, quality issues, and their overall impact on project performance. Establishing unified data governance frameworks will therefore facilitate future digital integration and support more reliable and comprehensive performance monitoring. By enabling integrated and high-quality datasets across project disciplines, such data architecture may create the conditions required for AI to become more structurally embedded within CQM systems in future applications.

Table (5-3) Evidence-Based Action Plan for Enhancing AI-Integrated Construction Quality Management

No	Research Result (Chapter 4 Evidence)	Recommendation	Implementation Approach (How to Do It)	Time Frame	Required Resources	Responsible Entity	Expected Outcome / Success Indicator
1	Strong positive impact of leadership commitment and quality culture on project outcomes; qualitative responses indicate uncertainty toward AI adoption at management level.	Establish Executive-Level Digital Quality Governance to guide AI integration within quality management systems.	Form a digital quality governance committee within program leadership; incorporate AI-supported dashboards and digital performance indicators into executive quality review meetings.	6–9 months	Governance framework documentation, AI dashboards, leadership workshops	Executive Management / Program Steering Committee	Digital quality governance structure formally established, and AI-based quality reports integrated into program review meetings.
2	SEM results show a significant direct effect of AI on project outcomes, but no moderating integration with CQM processes.	Integrate AI analytics into quality monitoring and reporting systems.	Deploy AI-supported analytics tools to analyze inspection results, defect patterns, and quality performance indicators; embed AI insights within project performance reports.	6–12 months	AI analytics platforms, integrated reporting systems, data management tools	PMO / Quality Management Department / IT Department	AI-generated insights are incorporated into routine quality performance monitoring and reporting processes.
3	Survey findings show heavy reliance on spreadsheets for quality tracking and relatively low use of integrated enterprise software systems.	Reduce spreadsheet dependency through integrated digital quality management platforms.	Gradually migrate inspection logs, NCR tracking, and quality documentation into centralized digital platforms integrated with project management systems.	9–12 months	Enterprise software systems, system integration support, database infrastructure	IT Department / Digital Transformation Unit	Centralized digital quality tracking system operational and reduction in manual spreadsheet-based reporting processes.
4	Lower mean scores for Corrective and Preventive Action (CAPA) processes compared with other CQM dimensions.	Strengthen data-driven CAPA mechanisms within quality management systems.	Establish centralized NCR databases and apply analytics tools to identify recurring defects, root causes, and preventive strategies.	12-16 months	NCR database systems, data analytics software, training programs	Quality Assurance and Quality Control Departments	Improved monitoring of recurring quality issues and implementation of preventive corrective action strategies.

No	Research Result (Chapter 4 Evidence)	Recommendation	Implementation Approach (How to Do It)	Time Frame	Required Resources	Responsible Entity	Expected Outcome / Success Indicator
5	Survey results indicate strong interest among professionals in learning AI tools but moderate levels of infrastructure readiness and training opportunities.	Develop AI competency programs for project and quality professionals.	Implement structured training initiatives covering AI tools, digital reporting platforms, and data analytics for quality engineers and project managers.	6–9 months	Training programs, digital learning platforms, external trainers or AI specialists	Human Resources / Quality / and IT Department	Increased AI literacy among project teams and improved ability to use digital tools in quality monitoring.
6	Fragmented data systems and inconsistent reporting structures limit digital integration and effective AI utilization.	Establish standardized data architecture for and Governance for Integrated Project Data.	Develop unified data standards, centralized repositories for disciplines data, and integration protocols connecting inspection, reporting, and performance systems.	12–24 months	Data governance framework, IT integration tools, database infrastructure	IT Governance Team / PMO	Standardized projects data structure enabling reliable digital analytics and future AI integration.

Source: developed by the author

While the recommendations presented in this section aim to strengthen the practical integration of Artificial Intelligence within Construction Quality Management systems, they also highlight several areas that require further academic investigation. In particular, the findings of this study suggest that the digital transformation of quality governance remains an evolving process, with important questions regarding data integration, organizational readiness, and governance frameworks still requiring deeper exploration. These observations provide a foundation for identifying several directions for future research in the field of AI-enabled construction quality management.

5.5 Future Research Directions

Based on the findings, limitations, and practical implications identified in this study, several research opportunities emerge that may contribute to advancing knowledge in AI enabled CQM systems. The results of this study suggest that the integration of AI within construction quality governance may evolve through progressive strategies rather than occurring as an immediate structural transformation.

Conceptually, this evolution may be understood through three stages of digital maturity as discussed in section 5.5.6. Stage 0 represents Traditional CQM, where governance relies primarily on conventional procedural frameworks and manual reporting systems. Stage 1 reflects AI-enhanced CQM, where artificial intelligence tools support analytics, monitoring, and decision-making but remain largely external to governance structures. Step 2 represents Integrated Digital Quality Governance, where AI becomes structurally embedded within quality management processes and may exert a moderating influence on project outcomes.

The empirical evidence of this study suggests that the examined projects are currently positioned within the AI-enhanced stage of digital maturity and transitioning toward Stage one. This observation highlights several research opportunities related to digital governance, organizational readiness, and the development of integrated frameworks capable of embedding AI within QMSs.

5.5.1 Longitudinal Studies of AI integration in CQM

The present study adopted a mixed method research design, that captured the relationship between CQM and AI, and Project outcomes at a specific point of time within JSWP. However, the integration of digital technologies within construction governance systems is a dynamic process that evolves throughout the lifecycle of projects and organizations. Future research may therefore employ longitudinal research designs to examine how the integration of AI within CQM systems develops over time. Such studies could provide deeper understanding and insight into whether the moderating influence of AI becomes stronger as organizations improve digital infrastructure, data integration, and governance maturity.

5.5.2 Comparative Studies Across Project Types & Organizational Context

This research focused primarily on large-scale infrastructure projects, which typically involve complex governance structures, multiple stakeholders, and significant technological resources. Future research could extend the analysis to different types of construction projects, including residential, industrial, and smaller scale projects. Comparative studies across project types, geographic regions, and organizational structures may help determine whether the relationship among CQM, AI and project outcomes may depend on project complexity, organizational maturity, digital capabilities or digital readiness.

5.5.3 Cross-Disciplinary Data Integration and Project Intelligence

Another promising direction for future research involves exploring integrated data architectures capable of combining information across multiple project disciplines. While quality management data provides valuable insights, combining data related to safety, schedule delays, productivity metrics, and cost controls may significantly enhance the analytical capabilities of digital systems. Future research may therefore investigate how integrated project data ecosystems can support cross-disciplinary analytics and enable AI systems to identify complex relationships among operational variables that can influence project performance.

5.5.4 Cybersecurity, Data Privacy, Digital Governance in AI driven QMS

As construction organizations increasingly adopt digital platforms and AI-supported analytics, issues related to cybersecurity, data privacy, and digital governance become increasingly important. Future research should examine governance frameworks capable of ensuring the responsible management and protection of project data. Investigating policies for secure data sharing, ethical AI use, and digital risk management may contribute to the development of more resilient and trustworthy AI-enabled QMSs.

5.5.5 Organizational Readiness & Capability Development for AI Adoption

Survey respondents in this study indicated a strong interest from project professionals in utilizing AI tools, while infrastructure readiness and formal training levels still remained low. Future research may therefore explore organizational readiness factors that influence successful AI adoption in construction management environments. Investigating leadership commitment, workforce capabilities, digital culture, and change management strategies could provide valuable insight into how organizations can effectively transition toward AI-supported quality governance.

5.5.6 Development and Empirical Testing for the Quality Intelligence Model (QIM)

Building on the empirical insights of this study, future research may explore integrated governance frameworks that embed AI within CQM systems. One potential direction involves conceptual development and empirical testing of the QIM. The concept of this model is introduced as a potential framework for integrating AI-enabled analytics with traditional quality management processes during the early stages of project planning and implementation. During this early-stage governance structures, quality strategies, project high level objectives, and risk management strategies are initiated.

Aligning AI capabilities with core CQM functions, the QIM framework aims to support predictive analytics, intelligent risk detection, and data driven decision-making throughout the lifecycle of the projects. Future studies may test and validate the QIM framework through case studies, pilot implementation, or comparative analysis across projects with varying levels of digital maturity in order to assess its potential contribution to the evolution of digitally augmented quality governance systems.

5.6 Limitations of the Study

While this study provides important empirical insights into the relationship between CQM, AI and Projects Outcomes, in large scale infrastructure projects, several limitations should be acknowledged when interpreting the findings.

First, the study employed a mixed method research design where data collected at a single point in time. Although this approach is common in organizational and project management research, it limits the ability to observe longitudinal changes in digital maturity and quality governance practices. The adoption and integration of artificial intelligence within CQM is an evolving phenomenon, and longitudinal studies could provide deeper understanding into how AI integration influences quantitative governance over different project phases.

Second, the research relied on survey-based responses obtained from project professionals involved in large infrastructure programs. While the sample included experienced participants from various roles and organizations, but survey data inherently dependent on respondents' perceptions and self-reported assessments of organizational practices. Also, measures were taken to ensure reliability and validity of constructs perceptual bias cannot be completely eliminated.

Third, although the study initially targeted a broader sample, several challenges were encountered during the survey data collection process, including low response rates, incomplete submissions, low quality of responses, and inconsistent responses patterns. A total of 190 completed survey responses were successfully received. After data screening, 23 responses were excluded due to incompleteness, low completion quality, or inconsistent response patterns. Accordingly, 167 valid responses were retained and used in the final quantitative analysis.

Fourth, while the final usable sample provided useful empirical insights for the exploratory case study context, it remains a limitation, particularly for testing the interaction effect of Artificial Intelligence as a moderating variable. Moderation effect often require larger sample sizes to detect small or emerging interaction patterns. Therefore, the statistical findings should be interpreted within the context of Jeddah

Stormwater Program and similar infrastructure projects, rather than as broad generalizations to the entire construction sector.

Finally, the study examined AI as an emerging organizational capability within CQM systems. Given the relatively early stage of AI adoption across many construction organizations, the operational maturity of digital tools varies significantly among projects. As a result, the moderating role of AI within quality governance structures may evolve as organizations continue to develop digital infrastructure and analytical capabilities. Despite these limitations, the study provides valuable empirical evidence regarding the evolving relationship between traditional quality management frameworks and emerging digital technologies in mega construction environments.

5.7 Chapter Summary and Concluding Remarks

This chapter presented a comprehensive discussion of the empirical findings of the study and examined their implications for CQM theory, artificial intelligence adoption, and governance practices in large infrastructure projects. The analysis confirmed that CQM remains a fundamental determinant of project performance, reinforcing the continued relevance of classical quality management principles derived from TQM, ISO systems, and foundational philosophies of quality gurus.

The empirical results showed that AI also contributes positively to project outcomes, indicating that digital technologies can enhance analytical capabilities and decision support processes within construction management environments. The findings also demonstrate how artificial intelligence can augment traditional CQM practices by converting dispersed operational data into predictive quality intelligence, supporting more proactive governance in complex infrastructure projects. However, the structural analysis reveals that AI does not yet significantly moderate the relationship between CQM and Project Outcomes. These findings suggest that digital technologies are currently functioning primarily as supportive analytical tools rather than as a fully embedded governance mechanism within QMS.

This discussion of findings highlighted a transitional stage in the evolution of quality governance within infrastructure programs. While traditional quality management frameworks remain structurally strong, the integration of advanced digital technologies is still developing. This observation aligns with emerging discussions in the literature concerning the transition toward Quality 4.0, where data driven technologies augment established quality CQM practices.

Building on these insights, the chapter presented theoretical contributions that extend existing knowledge in CQM and AI research. Practical implications were also outlined in the form of evidence-based recommendations aimed at strengthening governance structures, enhancing digital infrastructure integration, and developing organizational capabilities for AI-supported quality management.

Finally, the chapter introduced future research direction emphasizing the need to explore integrated frameworks that embed AI within QMS. In this context, the concept of the Quality Intelligence Model (QIM) was proposed as a potential research framework for examining how AI-enabled analytics can support predictive quality management and data driven decision-making in complex infrastructure projects. Further empirical investigations of such frameworks may contribute to the evolution of CQM from procedural governance toward intelligent, digitally augmented systems.

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APPENDICES



Exploring the Moderating Role of Artificial Intelligence

This questionnaire aims to understand Construction Quality Management (CQM) practices and changes, as well as the potential for utilizing artificial intelligence (AI) tools effectively to enhance various aspects of project quality management and their impact on project outcomes.

Your insights will help us identify current challenges and potential solutions for integrating AI in this crucial domain.

By: Eng. Ismail Hasan Ujaimi

PhD Candidate in Quality Management at Midocean University

Part A: Project Management Background & Experience

1. What is your role in the company?

- ☐ Director or Higher
- ☐ Senior Manager
- ☐ Manager
- ☐ Senior Engineer
- ☐ Engineer
- ☐ Inspector

* 2. What is your department?

- ☐ Management
- ☐ Construction
- ☐ Quality
- ☐ HSE
- ☐ Planing / Cost control
- ☐ Technical
- ☐ Other

* 3. What is the role of your organization in the project?

- ☐ Client
- ☐ PMO / PMC
- ☐ Supervision Consultant
- ☐ Contractor / Sub-Contractor
- ☐ Supplier

* 4. How many years of experience do you have?

- ☐ 0 - 5 Years
- ☐ 6 - 10 Years
- ☐ 11 - 15 Years
- ☐ 16 - 20 Years
- ☐ More than 20 years

* 5. What is your highest level of Education?

- ☐ PhD
- ☐ Masters
- ☐ Bachelor
- ☐ Diploma

* 6. What is the scale of the project based on the budget?
(based on MOMRA classification)

- ☐ Small < SR 50 million
- ☐ Medium SR 50 - 200 million
- ☐ Big > SR 200 million

* 7. What is the scale and complexity of the project team

- ☐ Small team (Less than 50 members)
- ☐ Medium team (50-150 members)
- ☐ Large team (150+ members)
- ☐ Large multinational team (150+ members)

8. Did you acquire any of the following certificates? (choose all that applies)

- ☐ PMP
- ☐ RMP
- ☐ Prince
- ☐ ISO Lead Auditor
- ☐ Lean Six Sigma
- ☐ Certified Manager of Quality
- ☐ Other (please specify)

9. If working on the Jeddah stormwater program please include the project name for analysis purposes?

* 10. What is your gender?

- ☐ Male
- ☐ Female



Exploring the Moderating Role of Artificial Intelligence

Part B1: Construction Quality Management “CQM” Practices Background:

Please indicate your level of agreement with the following statements (1 = Strongly Disagree, 5 = Strongly Agree)

* 11. Construction Quality Management “CQM” Practices Background

	Strongly Disagree	Disagree	Neutral / Not sure	Agree	Strongly Agree
Quality is considered a core value within my organization and supported by higher management	☐	☐	☐	☐	☐
Organizations’ Quality cultural patterns, like rituals, beliefs, values, and everyday procedures, directly or indirectly affect CQM practice?	☐	☐	☐	☐	☐
ISO 9001 certification among stakeholders positively contributes to orngasational and projects sucess	☐	☐	☐	☐	☐

* 12. We are facing the following challenges in maintaining quality across the current projects?

	Strongly Disagree	Disagree	Neutral / Not sure	Agree	Strongly Agree
Difficulty in identifying quality defects at early stages	☐	☐	☐	☐	☐
Challenges in managing and tracking defect resolution	☐	☐	☐	☐	☐
Difficulty ensuring compliance with standards/specifications	☐	☐	☐	☐	☐
Ineffectiveness in implementing corrective actions	☐	☐	☐	☐	☐
Lack of structured preventive action mechanisms	☐	☐	☐	☐	☐
Gaps in workforce skill level and training	☐	☐	☐	☐	☐
Absence of standardized quality strategies or best practices	☐	☐	☐	☐	☐

* 13. How frequently do you use the following tools or techniques for quality monitoring and analysis in your current project? Please rate based on your current project experience

	Not used	Rarely used	Sometimes used	Frequently used	Always used
Spreadsheets (e.g., Excel)	☐	☐	☐	☐	☐
KPIs Dashboards (Power BI / Tableau)	☐	☐	☐	☐	☐
Generic project software (e.g., MS Project, Primavera)	☐	☐	☐	☐	☐
Document-sharing platforms (e.g., SharePoint, Cloud storage, Google drive, Dropbox)	☐	☐	☐	☐	☐
Enterprise software (e.g., Oracle Unifier, Procore, Aconex)	☐	☐	☐	☐	☐

14. Which tool of the above mentioned do you find most effective, and why?

15. Please describe any specific challenges faced in implementing or improving quality practices?



Exploring the Moderating Role of Artificial Intelligence

Part B2: Dimensions of Construction Quality Management practices (Quality Planing - Quality Assurance - Quality Control - Quality Improvement)
Please indicate your level of agreement with the following statements (1 = Strongly Disagree, 5 = Strongly Agree)

* 16. To what extent do you agree with the following statements related to **Quality Planning** practices in your current project?

	Strongly Disagree	Disagree	Neutral / Not sure	Agree	Strongly Agree
There is a formal Quality Management System with clear Quality objectives, policy, procedures, and KPIs within the organization	☐	☐	☐	☐	☐
Project Quality Plans are prepared during the planning stage for each project	☐	☐	☐	☐	☐
We use defined quality objectives, performance indicators, and checklists	☐	☐	☐	☐	☐
Stakeholders are involved in the process of quality planning.	☐	☐	☐	☐	☐
Lessons learned from previous / similar projects are used	☐	☐	☐	☐	☐
Risk-based thinking is applied during quality planning to anticipate potential quality issues	☐	☐	☐	☐	☐
Quality planning includes clear roles, responsibilities, and communication plans	☐	☐	☐	☐	☐

* 17. To what extent do you agree with the following statements related to **Quality Assurance** practices in your current project?

	Strongly Disagree	Disagree	Neutral / Not sure	Agree	Strongly Agree
Quality audits are conducted regularly and effectively	☐	☐	☐	☐	☐
Management review meetings are conducted regularly and effectively	☐	☐	☐	☐	☐
Audit results are documented, communicated, and followed up with corrective or preventive actions	☐	☐	☐	☐	☐
There are procedures to evaluate and control the quality performance of contractors, subcontractors, and suppliers	☐	☐	☐	☐	☐
There are clear internal communication processes for enforcing quality standards	☐	☐	☐	☐	☐
Top management demonstrates strong commitment to quality assurance	☐	☐	☐	☐	☐

* 18. To what extent do you agree with the following statements related to **Quality Control** practices in your current project?

	Strongly Disagree	Disagree	Neutral / Not sure	Agree	Strongly Agree
There are a flow chart and procedures showing the process of quality control such as inspections, NCRs, SORs.	☐	☐	☐	☐	☐
Regular inspections and testing procedures are followed as per ITP	☐	☐	☐	☐	☐
Non-conformities are identified and corrected in a timely manner	☐	☐	☐	☐	☐
Documentation systems (e.g., NCR logs, SORs, issue logs) are consistently used to track quality issues	☐	☐	☐	☐	☐
Inspection and test results are reviewed and analyzed to identify trends and recurring issues	☐	☐	☐	☐	☐
Coordination occurs between site engineers, QA/QC staff, and contractors to resolve quality issues	☐	☐	☐	☐	☐

* 19. To what extent do you agree with the following statements related to **Quality Improvement** practices in your current project?

	Strongly Disagree	Disagree	Neutral / Not sure	Agree	Strongly Agree
Quality procedures are reviewed and updated regularly	☐	☐	☐	☐	☐
There are effective mechanisms for capturing feedback and lessons learned	☐	☐	☐	☐	☐
Training programs on quality standards are provided continuously	☐	☐	☐	☐	☐
Corrective and preventive actions (CAPA) are actively implemented and monitored	☐	☐	☐	☐	☐
Quality performance data is analyzed periodically to identify improvement opportunities	☐	☐	☐	☐	☐

Exploring the Moderating Role of Artificial Intelligence

Part C: Project Outcomes (Time-Cost-Quality-Customer satisfaction) and Perceived Impact of CQM Practices

Please indicate your level of agreement with the following statements regarding how current quality management practices have influenced project outcomes (1 = Strongly Disagree, 5 = Strongly Agree)

* 20. To what extent do you agree with the following statements related to the impact of Quality Management practices on **project cost** in your current project?

	Strongly Disagree	Disagree	Neutral / Not sure	Agree	Strongly Agree
Quality practices help in controlling project cost overruns by reducing reworks	☐	☐	☐	☐	☐
Rework due to quality issues increases project costs	☐	☐	☐	☐	☐
Cost-related risks due to poor quality are identified and mitigated proactively	☐	☐	☐	☐	☐
The organization tracks and reports both direct quality costs and indirect costs related to quality	☐	☐	☐	☐	☐

* 21. To what extent do you agree with the following statements related to the impact of Construction Quality Management practices on **project schedule**?

	Strongly Disagree	Disagree	Neutral / Not sure	Agree	Strongly Agree
The presence of robust CQM practices can reduce the frequency of rework and schedule overruns	☐	☐	☐	☐	☐
Quality-related delays (e.g., material rejection, repair, rework) are concerning in our project	☐	☐	☐	☐	☐
Early detection and resolution of quality issues contributes to avoiding negative schedule disruptions	☐	☐	☐	☐	☐

* 22. To what extent do you agree with the following statements related to the impact of Construction Quality Management practices on **overall project quality**?

	Strongly Disagree	Disagree	Neutral / Not sure	Agree	Strongly Agree
Robust CQM practices help in improving the overall quality of works	☐	☐	☐	☐	☐
Few defects are observed during project handover and included in the snag list	☐	☐	☐	☐	☐
Project outputs comply with specifications and quality standards	☐	☐	☐	☐	☐
Post-handover claims due to quality defects are minimal, as issues are addressed before final project handing over	☐	☐	☐	☐	☐

* 23. To what extent do you agree with the following statements related to **customer satisfaction** in your current project?

	Strongly Disagree	Disagree	Neutral / Not sure	Agree	Strongly Agree
CQM practices help to improve the overall quality of work, therefore increasing customer satisfaction	☐	☐	☐	☐	☐
Clients or end users express satisfaction with delivered quality	☐	☐	☐	☐	☐
Quality management improves stakeholder communication and satisfaction	☐	☐	☐	☐	☐
Customer feedback is regularly collected and used to improve project delivery and quality performance	☐	☐	☐	☐	☐



Exploring the Moderating Role of Artificial Intelligence

Part D: Potential AI Applications in Construction Quality Management Practices

Please indicate your level of agreement with the following statements (1 = Strongly Disagree, 5 = Strongly Agree)

* 24. To what extent do you agree with the following statements related to your **awareness and readiness** to adopt AI technologies in construction project quality management?

	Strongly Disagree	Disagree	Neutral / Not sure	Agree	Strongly Agree
I am interested in learning and using (AI) to enhance practices in my organization, including quality management	☐	☐	☐	☐	☐
I personally use AI tools such as ChatGPT and similars, to improve my productivity	☐	☐	☐	☐	☐
I am familiar with AI technologies (e.g., ML, NLP, computer vision, IoT)	☐	☐	☐	☐	☐
There are initiatives in Our organization to integrate AI in project process including quality	☐	☐	☐	☐	☐
Special training on using AI tools is needed for our staff	☐	☐	☐	☐	☐
Staff are competent and open to using AI tools in quality management	☐	☐	☐	☐	☐
The current system in your organization is ready to be integrated with AI technology	☐	☐	☐	☐	☐
The integration of AI can positively influence the project's outcomes and overall success	☐	☐	☐	☐	☐

* 25. To what extent do you agree with the following statements about how AI can be utilized throughout the quality lifecycle in construction projects?

	Strongly Disagree	Disagree	Neutral / Not sure	Agree	Strongly Agree
AI tools can be used for generating quality requirements from historical data	☐	☐	☐	☐	☐
AI Could help automating operations and digitalizing processes to improve productivity, safety, and quality	☐	☐	☐	☐	☐
AI Integration can help analyze quality data and identify trends and patterns	☐	☐	☐	☐	☐
AI Could help improve communication and collaboration between stakeholders on quality issues	☐	☐	☐	☐	☐
AI supports compliance checking with codes, standards, and projects specifications	☐	☐	☐	☐	☐
AI-powered dashboards are used for predictive insights during project execution	☐	☐	☐	☐	☐
AI tools help in detecting errors or defects earlier than traditional methods, especially if integrated with dashboards	☐	☐	☐	☐	☐
AI Integration help to predict and prevent errors related to humans, observations, non-conformities, before they occur	☐	☐	☐	☐	☐

* 26. To what extent do you agree with the following statements regarding the adoption of Artificial Intelligence (AI) in your organization and specifically within your Construction Quality Management (CQM) practices?

	Strongly Disagree	Disagree	Neutral / Not sure	Agree	Strongly Agree
Our organization’s top management is committed to exploring and supporting the use of AI	☐	☐	☐	☐	☐
There is strong organizational interest in applying AI in all processes including quality	☐	☐	☐	☐	☐
Implementation cost is a major concern that limits the adoption of AI	☐	☐	☐	☐	☐
Our current systems and tools can be integrated with AI with minimal adjustments	☐	☐	☐	☐	☐
There is a lack of internal AI-related training programs for staff	☐	☐	☐	☐	☐
We face challenges in collecting and organizing quality-related data that AI systems can use	☐	☐	☐	☐	☐
There are concerns about the accuracy and reliability of AI-generated quality insights	☐	☐	☐	☐	☐
Our organization sees AI as a future enabler for improving overall project delivery	☐	☐	☐	☐	☐
Current CQM workflow can be integrated with AI for better predictive control	☐	☐	☐	☐	☐
We are actively exploring partnerships or solutions to enhance AI capabilities	☐	☐	☐	☐	☐
Transparency, bias, reliability, accountability, ethical and legal considerations are biggest concerns for using AI	☐	☐	☐	☐	☐

27. What recommendations would you give for developing and implementing AI solutions for CQM effectively?

28. Please share any observations, insights, thoughts or experiences where AI improved or could have improved project outcomes?

Qualitative Thematic Analysis of JSWP Minutes of Meetings and Progress Reports

Convergent Mixed-Methods Triangulation — Thesis Chapter Support Document

Revised Edition — Full Corpus (243 Documents)

Program: Jeddah Stormwater Program (JSWP) **Analysis Scope:** 73 WSP QAQC Meeting Minutes + 169 Client Progress Meeting Minutes + 1 Survey Results Document **Total Documents Analysed:** 243 **Total Source Text Processed:** ~1.2 million characters **Total Quality-Related Statements Coded:** 11,090 **Analysis Date:** March 2026

Revision Note

This report supersedes the initial analysis (51 documents, 339 coded statements). The first pass covered only the WSP QAQC project-level meeting minutes. Upon verification, two additional document collections were identified and incorporated:

Collection	Documents	Period	Language	Previously Included
WSP Projects QAQC MOMs	73	Mar 2025 – Oct 2025	English	Partial (51 of 73)
Client Progress Meeting Minutes	169	Jan 2021 – Oct 2025	Arabic	None
Survey Results	1	2025	English	Yes
Total	243	2021–2025	Mixed	—

The Client Progress Meeting Minutes represent weekly programme-level meetings chaired by the client (PMO), covering all JSWP projects collectively. Their inclusion provides a five-year longitudinal view of quality management challenges at the programme governance level — a perspective entirely absent from the initial analysis.

Executive Summary

This report presents a five-step qualitative thematic analysis of the complete JSWP documentation corpus, conducted to support a Convergent Mixed-Methods research design for thesis research. Across 243 documents and 11,090 coded statements, ten distinct quality themes were identified. The analysis reveals that quality challenges in JSWP are not only widespread at the project execution level (as shown by the WSP QAQC MOMs) but are also deeply embedded in the programme’s governance and delivery culture, as evidenced by the five-year longitudinal record in the Client Progress Meeting Minutes.

The central finding is one of **strong convergence** between the qualitative evidence and the quantitative AI Risk Model outputs. The top three qualitative themes — Progress & Schedule Issues (n=3,176), Poor Workmanship (n=1,565), and Contractor Non-Compliance (n=1,354) — map directly to the three highest-impact predictors in the AI escalation model. Critically, the Client MOMs reveal that these problems have been present and discussed at the programme level since at least 2021, predating the current QAQC monitoring framework. This longitudinal persistence is a key finding for the thesis: the AI model is not detecting new problems but quantifying the risk profile of long-standing, structurally embedded quality challenges.

Step 1 — Document Corpus and Extraction Methodology

Corpus Overview

Collection	Documents	Coded Statements	% of Total Statements
Client Progress Meeting Minutes (Arabic)	169	9,267	83.6%
WSP QAQC Meeting Minutes (English)	73	1,645	14.8%
Survey Results (English)	1	178	1.6%
Total	243	11,090	100%

Extraction Methodology

Text was extracted from all 243 Word-format documents (.docx and .docm) using XML-level parsing of the Office Open XML structure, bypassing macro-enabled format restrictions. For Arabic documents, the full Unicode text was preserved and coded against a bilingual keyword vocabulary (Arabic and English). Sentences were segmented on punctuation boundaries and table-row delimiters, filtered to 20–600 characters, and tested against a 130-keyword thematic coding vocabulary distributed across ten themes.

Project Coverage

Project	WSP MOM Documents	Client MOM Documents	Total
Al-Hamrah	16	—	16
Hail	21	—	21
Al-Huda	17	—	17
Al-Rawdah	2	—	2
North Channel	2	—	2
Al-Marwah	3	—	3
Al-Falah	2	—	2
South Obhur	3	—	3
King Faisal Road	1	—	1
Al-Abruq	4	—	4
Programme-Wide	2	169	171
Total	73	169	242

Step 2 — Thematic Coding

Methodology

Each extracted statement was tested against a bilingual (Arabic/English) vocabulary of 130 keyword patterns across ten themes. Themes were derived from the established Construction Quality Management literature and calibrated to the JSWP operational context. A statement could be assigned to multiple themes.

Thematic Frequency Table — Full Corpus

Rank	Theme	Frequency	Documents	% of Docs	Prevalence
1	Progress & Schedule Issues	3,176	201	83%	Very High
2	Poor Workmanship	1,565	231	95%	Very High
3	Contractor Non-Compliance	1,354	227	93%	Very High
4	Safety & Environmental	1,330	195	80%	Very High
5	Inspection Failures	1,257	225	93%	Very High
6	Coordination Problems	1,207	206	85%	Very High
7	Delayed Corrective Actions	465	221	91%	High
8	Resource Constraints	412	131	54%	Moderate
9	Management Escalations	248	112	46%	Moderate
10	Material Approval Delays	76	68	28%	Low
Total		11,090	—	—	—

Critical observation: Six of the ten themes appear in more than 80% of all 243 documents. This near-universal prevalence is not characteristic of isolated or project-specific problems — it is the signature of systemic, programme-wide quality management failures that have persisted across a five-year period and across all JSWP projects.

Comparison: Initial vs. Full Corpus Analysis

The inclusion of the Client MOMs fundamentally changes the frequency ranking and reveals the programme-level perspective:

Theme	Initial (51 docs)	Full Corpus (243 docs)	Change	New Insight
Contractor Non-Compliance	106 (Rank 1)	1,354 (Rank 3)	+1,248	Still dominant at project level; surpassed by schedule/workmanship at programme level
Poor Workmanship	61 (Rank 2)	1,565 (Rank 2)	+1,504	Most pervasive theme across all document types
Progress & Schedule Issues	Not coded	3,176 (Rank 1)	New	Client MOMs reveal schedule pressure as the dominant programme-level concern
Material Approval Delays	52 (Rank 3)	76 (Rank 10)	+24	Less prominent at programme level; concentrated in project-level QAQC discussions
Safety & Environmental	Not coded	1,330 (Rank 4)	New	Client MOMs include HSE reporting absent from QAQC MOMs

Representative Statements by Theme

Progress & Schedule Issues (n=3,176, 201 documents)

The dominance of this theme in the Client MOMs reflects the PMO's primary concern with programme delivery milestones. Arabic-language discussions consistently reference project completion percentages, delayed handovers, and contractor schedule non-compliance. English QAQC MOMs add the quality dimension: schedule pressure from contractors leads to shortcuts in inspection compliance and material approval processes.

- *Al-Hamrah, Oct 2025*: "WSP ask for updated schedule for follow-up. CWC will provide a schedule for the status of the cover for PRD and MH."
- *Client MOM, 2024 (Arabic)*: Programme-level discussion of project completion percentages and delayed milestones across multiple JSWP packages.
- *Hail, Apr 2025*: "A meeting is to be arranged with WSP team regarding PMO's NCR & SOR closure process on Monday 27/04/2025 at 2:30 PM."

Poor Workmanship (n=1,565, 231 documents — 95% coverage)

This theme's appearance in 95% of all documents makes it the single most pervasive quality issue in the programme. It spans both the project-level QAQC discussions (specific defects in asphalt, compaction, concrete, and pipe installation) and the programme-level client meetings (general references to quality standards and rectification requirements).

- *Al-Hamrah, Aug 2025*: "Implementation Quality of asphalt works on Line AH01-5-1 PRD. CWC started cutting asphalt for rectification as per WSP road Engineer instruction."
- *Al-Huda*: "Works Methodologies statement approvals & logs. Concrete Mixed design approvals & logs. Independent third-party lab or Site lab testing materials — approvals."
- *Al-Hamrah, Jun 2025*: "Rectification work has been started for the storage area. CWC. 1/7/2025. Open."

Contractor Non-Compliance (n=1,354, 227 documents — 93% coverage)

Present in 93% of all documents, this theme confirms that contractor non-compliance is not a project-specific aberration but a programme-wide behavioural pattern. The QAQC MOMs provide specific evidence (repeated "Continues Action" items, NCR/SOR log follow-up), while the Client MOMs show that the PMO has been aware of and discussing contractor compliance issues since 2021.

- *Al-Hamrah, Mar 2025*: "CWC shall rectify or replace Stockpile area sieves mesh and repeated violation."
- *Al-Hamrah, Mar 2025*: "CWC shall use approved capacity Roller equipment for compaction Earth works. CWC Continues Action."
- *North Channel, Apr 2025*: "SAJCO provided the work inspection request to the quality team in WSP in order to close out SOR."

Inspection Failures (n=1,257, 225 documents — 93% coverage)

The near-identical document coverage of Contractor Non-Compliance and Inspection Failures (both 93%) suggests these two themes are structurally linked: contractor non-compliance manifests most frequently as inspection failures, and inspection failures are the primary mechanism by which SORs escalate to NCRs.

- *Al-Hamrah, Mar 2025*: "CWC provided the work inspection request for MH 19 in Line Ah01 and MH 21, MH20, MH 19 Line AH07 to the quality team in WSP in order

to close out SOR 224 and SOR 225.”

- *Al-Falah, Apr 2025*: “GRP for ⁵⁰⁰/₃₀₀ Dia shall be tested as per the approved ITP. UPVC 400 Dia Ground water line shall be arranged mandrel test as per project specs.”
- *Al-Rawdah, Mar 2025*: “The contractor must issue WIR with full coordination with the consultant before any construction step.”

Delayed Corrective Actions (n=465, 221 documents — 91% coverage)

Despite its lower frequency relative to the top themes, Delayed Corrective Actions appears in 91% of all documents — the third-highest document coverage of any theme. This indicates that while individual instances are less frequent, the problem of unclosed corrective actions is nearly universal across the programme.

- *Al-Hamrah, Mar 2025*: “The LOG for NCR/SOR should be available during weekly meeting to discuss and follow up for closeout.”
- *Al-Hamrah, Mar 2025*: “QC Statistics: Total Closed Open — SORs 14, 7, 7; NCRs 14, 7, 7.”
- *Al-Abruq*: Multiple consecutive MOMs showing the same action items carried forward as “Open.”

Material Approval Delays (n=76, 68 documents — 28% coverage)

The relatively low frequency of this theme in the full corpus (compared to its prominence in the initial QAQC-only analysis) reveals an important distinction: material approval is primarily a project-level quality management concern discussed in QAQC meetings, not a programme-level governance concern discussed in client progress meetings. This does not diminish its importance — the AI model identifies it as the highest-escalation technical warning type (58.3%) — but it explains why it is less visible at the PMO level.

Step 3 — Theme-to-Issue Mapping

Mapping Table

Qualitative Theme	Related Issue Category	AI Warning Type	Escalation Rate	Domain	Alignment
Progress & Schedule Issues	Overdue Issues / Delay	Delay	66.7%	D-QMS	Strong
Poor Workmanship	General Quality	General Quality	47.7%	D-RST	Strong
Contractor Non-Compliance	High Contractor Risk	Coordination Issue	33–72%	D-QMS	Strong
Safety & Environmental	General Quality	General Quality	47.7%	D-HSE	Moderate
Inspection Failures	Inspection Failure	Inspection Failure	49.0%	D-QMS	Strong
Coordination Problems	Coordination Issue	Coordination Issue	33.3%	D-CON	Moderate
Delayed Corrective Actions	Overdue Issues	Delay	66.7%	D-QMS	Strong
Resource Constraints	General Quality	General Quality	47.7%	D-QMS	Moderate
Management Escalations	High Escalation Risk	Delay	66.7%	D-QMS	Moderate
Material Approval Delays	Material Risk	Material Risk	58.3%	D-MAT	Strong

Key Mapping Insights

The mapping reveals two structural patterns that are critical for the thesis argument. First, the three highest-frequency qualitative themes (Progress & Schedule Issues, Poor Workmanship, Contractor Non-Compliance) all map to warning types with

escalation rates above 47% — confirming that the issues most discussed in meetings are also the issues most likely to escalate into formal non-conformances. Second, the theme with the lowest qualitative frequency (Material Approval Delays, n=76) maps to the warning type with the highest technical escalation rate (58.3%), suggesting that while material approval issues are discussed less frequently in meetings, they are disproportionately dangerous when they do occur.

Survey Corroboration

The survey results (n=167 respondents, Cronbach's $\alpha=0.949$) provide additional bridging evidence across the theme-to-issue mapping:

Survey CQM Dimension	Mean Score	%	Relevance to Thematic Mapping
AI Utilization	3.93	78.6%	Supports thesis argument for AI-based QI Model
Quality Control	3.88	77.6%	High score yet widespread inspection failures — execution gap
Quality Planning	3.82	76.4%	Plans exist but not followed — contractor non-compliance
Quality Assurance	3.76	75.2%	Audit findings unclosed — audit-escalation linkage
Quality Improvement	3.61	72.2%	Lowest score — confirms corrective action system failure

The survey's finding that Quality Improvement is the weakest CQM dimension (Mean=3.61) is the most significant corroborating data point: it directly confirms the qualitative evidence that corrective actions are not being effectively closed and that recurring issues are not being systematically eliminated.

Step 4 — Triangulation Analysis

Triangulation Table — Full Corpus

Quantitative Finding	Qualitative Evidence	Interpretation
Delay warnings: highest escalation rate (66.7%)	Progress & Schedule Issues is the most frequent theme (n=3,176, 83% of docs). Client MOMs show 5 years of schedule pressure discussions.	Schedule pressure is the primary programme-level driver of quality risk. When contractors are behind schedule, they bypass inspection and approval requirements, directly triggering the escalation pathway.
Poor Workmanship: 47.7% escalation rate; widespread in NCRs	Poor Workmanship is the most pervasive theme (n=1,565, 95% of docs). Appears in virtually every document across all projects and years.	Workmanship quality is a chronic, programme-wide failure. Its near-universal document coverage (95%) confirms this is not a contractor-specific or project-specific problem but a systemic delivery quality issue.
Contractor risk: dominant predictor (impact score 92); high-risk contractors escalate 3× more	Contractor Non-Compliance appears in 93% of all documents (n=1,354). Client MOMs show this has been discussed at PMO level since 2021.	Contractor behaviour is the root cause of the majority of escalations. The 5-year longitudinal evidence from Client MOMs confirms this is a structural, not incidental, programme risk. The AI model is quantifying a problem that has been visible in meeting records for years.
Inspection Failure: 7-day escalation window	Inspection Failures appears in 93% of documents (n=1,257). QAQC MOMs show WIR non-compliance as a recurring pattern.	The 7-day escalation window is a procedural consequence of inspection non-compliance. The near-identical document coverage of Contractor Non-Compliance and Inspection Failures (both 93%) confirms these are two manifestations of the same underlying behavioural problem.
Material Risk: 58.3% escalation rate	Material Approval Delays appears in 28% of documents (n=76) —	Material approval failures are a project-level technical risk, not a programme-level governance concern. Their low visibility in

Quantitative Finding	Qualitative Evidence	Interpretation
(highest technical rate)	concentrated in QAQC MOMs, not Client MOMs.	Client MOMs explains why they may be under-managed at the PMO level despite carrying the highest technical escalation rate. This is a key thesis finding: the PMO's governance view and the QAQC operational view diverge most sharply on material risk.
85% of warnings are in projects with overdue audit findings	Delayed Corrective Actions appears in 91% of documents (n=465). Audit findings from July 2025 remain 100% open.	Audit closure requires the same corrective actions that are themselves overdue. The 91% document coverage of Delayed Corrective Actions confirms that the corrective action system failure is programme-wide, explaining why audit findings cannot be closed.
Program QI = $\frac{45}{100}$ (At Risk); escalation rate = 49.6%	Management Escalations (n=248, 46% of docs). Survey: Quality Improvement lowest CQM dimension ($3.\frac{61}{5.00}$).	The low Program QI reflects the cumulative effect of all qualitative themes operating simultaneously across the programme. The survey confirms that the programme lacks effective improvement mechanisms — it manages quality reactively rather than proactively.
Coordination Issue: lowest escalation rate (33.3%)	Coordination Problems appears in 85% of documents (n=1,207) but with lower severity per instance.	The high document coverage but low escalation rate for coordination issues confirms that coordination problems are being identified and discussed in meetings before they reach formal NCR status. The MOM format is effective at containing coordination issues — its least effective function is closing corrective actions.

Step 5 — Narrative Insight Summary

The Five-Year Longitudinal View: What the Client MOMs Reveal

The most significant finding from the full corpus analysis is that the quality challenges currently being detected by the AI Risk Model are not new. The Client Progress Meeting Minutes — 169 weekly Arabic-language meetings spanning January 2021 to October 2025 — show that Poor Workmanship, Contractor Non-Compliance, and Progress & Schedule Issues have been recurring discussion items at the PMO level throughout the programme's lifecycle. This longitudinal evidence transforms the thesis argument: the AI model is not predicting novel risks but is providing a systematic, quantified framework for risks that have been visible in meeting records for years without being effectively resolved.

This finding has profound implications for the thesis's contribution. It demonstrates that the problem is not a lack of information — the PMO has been receiving weekly reports on these issues for five years — but a lack of a structured analytical framework to translate that information into predictive risk intelligence. The Quality Intelligence Model addresses precisely this gap.

How MOM Discussions Support the AI Model Results

The Schedule-Quality Nexus. The dominance of Progress & Schedule Issues (n=3,176, 83% of documents) in the full corpus reveals a mechanism not visible in the QAQC-only analysis: schedule pressure is the primary driver of quality shortcuts. When contractors are behind schedule — as evidenced by five years of PMO-level schedule discussions — they bypass inspection requirements, proceed with unapproved materials, and delay corrective actions. The AI model captures the downstream consequences of this behaviour (inspection failures, material risk warnings, delay escalations), while the Client MOMs document the upstream cause (persistent schedule non-compliance). Together, they establish a causal chain from schedule pressure to quality escalation.

The Workmanship-Escalation Pathway. Poor Workmanship's appearance in 95% of all documents — the highest document coverage of any theme — establishes it as the most pervasive quality failure in the programme. The QAQC MOMs provide specific evidence of defects (asphalt rectification, compaction failures, concrete mix non-compliance), while the Client MOMs show that workmanship quality has been a

standing agenda item at the PMO level throughout the programme. The AI model's General Quality warning type (47.7% escalation rate) captures this theme quantitatively, but the qualitative evidence reveals that workmanship failures are the visible manifestation of deeper systemic issues: inadequate contractor supervision, insufficient quality control resources, and the absence of effective quality improvement mechanisms.

The Contractor Behaviour Pattern. Contractor Non-Compliance in 93% of documents over five years establishes a clear behavioural pattern: the contractors engaged in JSWP have consistently failed to comply with quality requirements across multiple projects, multiple years, and multiple contract packages. The AI model's identification of contractor performance as the dominant escalation predictor (impact score 92, $3\times$ escalation multiplier for high-risk contractors) is not a statistical artefact — it is the quantification of a behavioural pattern that has been documented in meeting records since 2021. The qualitative evidence from Client MOMs confirms that this pattern was known at the PMO level but not effectively addressed through the existing quality management framework.

The Corrective Action System Failure. Delayed Corrective Actions appears in 91% of all documents — the third-highest document coverage. This near-universal presence, combined with the survey's finding that Quality Improvement is the weakest CQM dimension ($3.61/5.00$), confirms a structural failure in the programme's corrective action system. Items are identified, documented, and discussed in meetings, but they are not being effectively closed. The AI model captures this as the highest-escalation warning type (Delay, 66.7%), confirming that the failure to close corrective actions is not merely an administrative inconvenience but the single highest-risk pathway to formal NCR escalation.

The PMO-QAQC Perception Gap. A key finding that emerges from comparing the two document collections is a significant divergence in what is visible at the PMO level versus the QAQC operational level. Material Approval Delays — the highest-escalation technical warning type (58.3%) — appears in only 28% of documents and is concentrated in QAQC MOMs, not Client MOMs. This means that the PMO's weekly governance meetings are not surfacing the issue that the AI model identifies as the most dangerous technical risk. Conversely, Progress & Schedule Issues — the dominant theme in Client MOMs — is not a formal warning type in the AI model, suggesting that the model is capturing the downstream quality consequences of schedule pressure without explicitly modelling the schedule pressure itself. These

gaps represent opportunities for the Quality Intelligence Model to bridge the PMO-QAQC information divide.

Key Recurring Operational Problems

Based on the integrated analysis of 243 documents across five years, five structural quality problems emerge as the primary drivers of programme risk:

1. Chronic Schedule Non-Compliance Driving Quality Shortcuts. The five-year record of schedule discussions in Client MOMs, combined with the AI model's identification of Delay warnings as the highest-escalation type (66.7%), establishes schedule pressure as the root cause of the majority of quality failures. Contractors behind schedule bypass quality requirements, creating a cascade of inspection failures, material approval shortcuts, and delayed corrective actions.

2. Systemic Workmanship Deficiencies Across All Projects. Poor Workmanship's 95% document coverage over five years indicates that workmanship quality is a programme-wide structural failure, not a contractor-specific or project-specific problem. This suggests that the root cause lies in programme-level factors: contractor selection criteria, supervision intensity, quality control resourcing, and the absence of effective quality improvement mechanisms.

3. Persistent Contractor Non-Compliance Without Effective Consequences. Contractor Non-Compliance in 93% of documents over five years, with the same contractors (CWC, SAJCO) repeatedly cited, indicates that the current corrective action framework is insufficient to change contractor behaviour. The AI model's 3× escalation multiplier for high-risk contractors quantifies the cost of this failure.

4. Corrective Action System Failure at All Levels. The 91% document coverage of Delayed Corrective Actions, combined with 100% open audit findings (8+ months overdue), confirms that the programme's corrective action system is not functioning at any level — project, programme, or audit. This is the single most actionable finding for the PMO: the quality management system has the right structure but lacks the enforcement mechanisms to drive closure.

5. PMO-QAQC Information Divide. The divergence between what is discussed in Client MOMs (schedule, workmanship, contractor behaviour) and what is tracked in QAQC MOMs (material approvals, inspection compliance, NCR/SOR closure) represents a structural information gap. The PMO is managing quality at the governance level

without full visibility of the technical risk signals that the AI model identifies as the highest-escalation indicators. The Quality Intelligence Model addresses this gap by providing a unified analytical framework that integrates both perspectives.

Summary of Deliverables

Deliverable 1: Thematic Frequency Table — Full Corpus

Rank	Theme	Frequency	Documents	% of Docs
1	Progress & Schedule Issues	3,176	201	83%
2	Poor Workmanship	1,565	231	95%
3	Contractor Non-Compliance	1,354	227	93%
4	Safety & Environmental	1,330	195	80%
5	Inspection Failures	1,257	225	93%
6	Coordination Problems	1,207	206	85%
7	Delayed Corrective Actions	465	221	91%
8	Resource Constraints	412	131	54%
9	Management Escalations	248	112	46%
10	Material Approval Delays	76	68	28%

Deliverable 2: Theme-to-Issue Mapping

Theme	Issue Category	Warning Type	Escalation Rate	Alignment
Progress & Schedule Issues	Overdue Issues	Delay	66.7%	Strong
Poor Workmanship	General Quality	General Quality	47.7%	Strong
Contractor Non-Compliance	High Contractor Risk	Coordination Issue	33–72%	Strong
Inspection Failures	Inspection Failure	Inspection Failure	49.0%	Strong
Delayed Corrective Actions	Overdue Issues	Delay	66.7%	Strong
Material Approval Delays	Material Risk	Material Risk	58.3%	Strong
Coordination Problems	Coordination Issue	Coordination Issue	33.3%	Moderate
Management Escalations	High Escalation Risk	Delay	66.7%	Moderate

Deliverable 3: Triangulation Table

Quantitative Finding	Qualitative Evidence	Interpretation
Delay: 66.7% escalation rate	Progress & Schedule Issues: 3,176 stmts, 83% of docs, 5-year record	Schedule pressure is the primary upstream driver of quality escalation
Poor Workmanship: 47.7% escalation, widespread in NCRs	Poor Workmanship: 1,565 stmts, 95% of docs	Most pervasive quality failure; systemic, not project-specific
Contractor risk: dominant predictor (score 92)	Contractor Non-Compliance: 1,354 stmts, 93% of docs, since 2021	Chronic behavioural pattern; AI model quantifies a known but unresolved risk
Inspection Failure: 7-day escalation window	Inspection Failures: 1,257 stmts, 93% of docs	Procedural escalation pathway triggered by contractor non-compliance
Material Risk: 58.3% escalation (highest technical)	Material Approval Delays: 76 stmts, 28% of docs (QAQC only)	PMO-QAQC information gap: highest technical risk is invisible at governance level
85% warnings in overdue-audit projects	Delayed Corrective Actions: 465 stmts, 91% of docs	Corrective action system failure prevents audit closure
Program QI = $\frac{45}{100}$ (At Risk)	Survey: Quality Improvement lowest CQM dim. ($3.\frac{61}{5.00}$)	Programme lacks systematic improvement mechanisms

Deliverable 4: Narrative Insight Summary

See Section “Step 5 — Narrative Insight Summary” above for the full narrative.

Core thesis-supporting conclusion: The qualitative thematic analysis of 243 JSWP documents (2021–2025) provides strong convergent validity for the AI Risk and Escalation Model across all eight triangulation points. The five-year longitudinal record from Client Progress Meeting Minutes reveals that the quality challenges quantified by the AI model are not new — they are structurally embedded programme risks that have been visible in meeting records since 2021. The Quality Intelligence Model’s contribution is not the discovery of these risks but the

provision of a systematic, quantified, and predictive analytical framework that transforms five years of meeting-level observations into actionable risk intelligence.

Methodological Note for Thesis Chapter

This analysis follows the **Convergent Parallel Mixed Methods Design** (Creswell & Plano Clark, 2018), in which quantitative and qualitative data are collected and analysed independently, then merged at the interpretation stage. The analysis demonstrates **strong convergence** across all six primary triangulation points, with two additional findings of **moderate convergence** for coordination and management escalation themes.

The bilingual corpus (Arabic Client MOMs + English QAQC MOMs) required a bilingual keyword coding vocabulary. Arabic statements were coded using Arabic-language quality management terminology; the thematic categories themselves are language-independent. The coding vocabulary was validated against the known JSWP issue taxonomy (D-QMS, D-MAT, D-RST, D-CON, D-HSE domain codes) to ensure alignment between qualitative themes and quantitative issue categories.

For the thesis chapter, this analysis is recommended for inclusion in the **Mixed Methods Triangulation** section, following the presentation of quantitative AI model results. The five-year longitudinal finding from Client MOMs is particularly suitable for the **Discussion** chapter, where it supports the argument that a Quality Intelligence Model provides value not by identifying new risks but by systematically quantifying and predicting risks that have been present but inadequately managed throughout the programme's lifecycle.

Document prepared for thesis research purposes. Data sources: JSWP WSP QAQC Meeting Minutes (73 documents, Google Drive), JSWP Client Progress Meeting Minutes (169 documents, Google Drive, Arabic), Survey Results (Dr. Ismail Hasan, 2025), JSWP Structured Issue Dataset (673 NCRs/SORs), AI Risk Model outputs (113 warnings, DSS Model F).

JSWP Quality Intelligence Model

Comprehensive Development Report — From Data Inventory to Operational Dashboard

Program: Jeddah Stormwater Program (JSWP)

Document Type: Thesis-Grade Technical Report

Prepared by: Ismail Ujaimi

Date: April 2026

Version: 2.0

Executive Summary

This report documents the complete development lifecycle of the JSWP Quality Intelligence Model, a thesis-grade analytical framework built to transform fragmented quality assurance logs into actionable intelligence for program management and academic research. The model integrates structured issue data, unstructured meeting minutes, audit findings, and AI-powered risk prediction into a unified dashboard and decision support system.

What was built: A multi-layered quality intelligence system comprising (1) a standardized data warehouse of 673 quality issues across 35 projects, (2) an AI risk and escalation prediction model analyzing 113 warnings, (3) a thematic analysis of 243 meeting minutes covering 2021–2025, and (4) an interactive web dashboard with 9 analytical views.

Why it matters: The JSWP program exhibited a 90% overdue closure rate and 49.6% escalation rate from warnings to NCRs, indicating systemic quality management failures. This model provides the first quantitative evidence linking governance failures (unresolved meeting warnings and audit findings) to field defects, enabling both operational intervention and academic contribution.

Key findings:

- **Escalation behavior is the primary driver of program risk**, contributing 24.8 points of penalty to the Program Quality Index
 - **Contractor performance variation is extreme**, with Quality Index scores ranging from 45 (At Risk) to 100 (Excellent)
 - **Qualitative and quantitative evidence converge strongly** across all 6 major triangulation points, validating the model's construct validity
 - **Five years of meeting minutes** (2021–2025) show that the problems quantified by the AI model are not new — they are structurally embedded risks discussed weekly but inadequately managed
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1. Project Context and Objectives

1.1 Program Background

The Jeddah Stormwater Program (JSWP) is a large-scale infrastructure program managed by the Royal Commission for Jeddah (RCJ) and delivered through multiple contractors and consultants. Quality assurance and quality control (QA/QC) processes generate three primary types of quality records:

- **Non-Conformance Reports (NCRs)** — formal defect notices requiring contractor rectification
- **Site Observation Reports (SORs)** — lower-severity quality observations
- **Site Instructions (SIs)** — administrative directives

These records are logged in multiple systems: a PMO master log maintained by the program management office, and individual supervision logs maintained by consulting firms overseeing specific project packages. Additionally, quality governance processes generate:

- **Minutes of Meetings (MOMs)** — weekly progress and QAQC coordination meetings
- **Audit Reports** — periodic third-party quality system audits
- **Monthly Progress Reports** — contractor performance summaries

1.2 Research Problem

The program exhibited persistent quality management challenges:

1. **Data fragmentation** — quality issues logged in 12+ different Excel files with inconsistent naming, missing fields, and duplicate entries
2. **Reactive management** — quality interventions occurred only after field defects materialized, not when early warning signs appeared in meetings or audits
3. **No performance benchmarking** — no systematic comparison of contractor or project quality performance
4. **Lack of predictive capability** — no ability to forecast which projects or contractors would generate future NCRs

5. **Qualitative evidence disconnected from quantitative metrics** — meeting discussions and audit findings were not linked to issue data

1.3 Research Objectives

The Quality Intelligence Model was designed to address these gaps through three objectives:

Operational Objective: Provide PMO leadership with a real-time dashboard showing quality risk signals, contractor performance rankings, and bottleneck identification to enable proactive intervention.

Analytical Objective: Build an AI-powered decision support system that predicts escalation probability and time-to-escalation for quality warnings, proving the statistical relationship between governance failures and field defects.

Academic Objective: Demonstrate a convergent mixed-methods research design where qualitative thematic analysis of meeting minutes triangulates with quantitative AI model findings, providing robust construct validity for the Quality Intelligence framework.

2. Stage 1: Data Inventory and Profiling

2.1 Source Data Discovery

The first stage involved systematic discovery and profiling of all available quality data sources. The inventory revealed:

Data Source	Format	Records	Period	Language	Completeness
PMO NCR Log	Excel	83	2019–2024	English	High (95%)
PMO SOR Log	Excel	220	2019–2024	English	Medium (78%)
PMO SI Log	Excel	3	2024	English	Low
Supervision Logs (11 files)	Excel	397	2021–2024	English	Variable (45–85%)
WSP QAQC Meeting Minutes	Word (docm)	73	Mar–Oct 2025	English	N/A (text)
Client Progress Meetings	Word (docx)	169	2021–2025	Arabic	N/A (text)
Audit Reports	PDF	5	Jul 2025	English	N/A (text)
Survey Results	Word (docx)	1	2025	English	N/A (text)

Total structured records: 703 (before deduplication)

Total unstructured documents: 248

2.2 Data Quality Assessment

Profiling revealed significant data quality challenges:

Project naming inconsistency: Over 40 different spellings for the same projects (e.g., “30 loc”, “almohammadeya”, “AL MOHAMMADIYAH”, “Up03/D 006” all referring to the same project). This required building a canonical project dictionary mapping all variants to 35 standardized `project_id` values.

Contractor aliases: 14 distinct contractors were identified, but supervision logs often lacked contractor information entirely, resulting in 370 issues (55%) initially classified as “UNKNOWN” contractor until cross-referenced with project-level contract data.

Missing dates: 18% of supervision log records lacked a `date_issued` field, requiring inference from adjacent records or exclusion from time-series analysis.

Status ambiguity: Raw status values included “cl”, “op”, “opened”, “ongoing”, “closed”, “Closed”, and blank cells, all requiring standardization to a binary `open` /

Closed classification.

Duplicate entries: Cross-checking PMO logs against supervision logs revealed 30 duplicate records where the same NCR was logged in both systems.

2.3 Initial Findings

Three critical patterns emerged from the profiling stage that shaped the entire model design:

1. **Extreme overdue rate:** 89.4% of all issues missed their target closure date, indicating a systemic program-level problem rather than isolated contractor failures
2. **Recurrence pattern:** 42.4% of closed SORs recurred within 30 days with the same contractor, suggesting that closure was administrative rather than corrective
3. **Escalation pathway:** Manual review of 50 random NCRs showed that 34 (68%) were preceded by SOR warnings or MOM discussion items within 14 days, suggesting a predictable escalation pattern

These findings directly informed the decision to prioritize **escalation prediction** (Model F) and **recurrence analysis** (Model B) over other potential use cases.

3. Stage 2: ETL Pipeline and Data Standardization

3.1 Pipeline Architecture

A Python-based ETL (Extract, Transform, Load) pipeline was developed to merge all structured sources into a single `fact_issues` master table. The pipeline followed a strict processing sequence:

Extract: Read all 12 Excel files using `pandas`, preserving original column names and data types for audit traceability.

Standardize: Apply canonical mapping dictionaries to force all project names, contractor names, and status values into standardized primary keys.

Deduplicate: Apply a hierarchy rule (PMO > Consultant) to remove duplicate records, keeping the PMO version as the authoritative source.

Calculate: Derive computed fields including `issue_age_days` , `days_to_close` , and `overdue_flag` based on business rules.

Validate: Run data quality checks including referential integrity (all `project_id` values exist in `dim_project`), date logic (no `date_closed` before `date_issued`), and completeness thresholds (minimum 70% non-null for critical fields).

Load: Export clean datasets to CSV and Excel formats for downstream use.

3.2 Standardization Logic

The standardization phase was the most labor-intensive component of the ETL process, requiring domain expertise to resolve ambiguous mappings.

Project standardization involved building a 127-entry mapping dictionary. For example, all of the following raw values were mapped to the canonical `project_id = "AL_MOHAMADIYAH"` :

- “30 loc”
- “almohammadeya”
- “AL MOHAMMADIYAH”
- “Up03/D 006”
- “AL-MOHAMMADIYAH”
- “Mohammadiyah”

The final project dimension table contained 35 unique projects, with the top 5 by issue volume being AL_MOHAMADIYAH (85 issues), AL_BASATEEN (57), HAIL (53), MLG4 (43), and AL_HAMRA (43).

Contractor standardization followed a similar approach, mapping variations like “SAJCO”, “Saudi Arabian Joint Contracting”, and “sajco” to the canonical `contractor_id = "SAJCO"` . The final contractor dimension table contained 14 unique contractors, with SAJCO (59 issues), AJ Trading (55), CEPCO (44), SALCO (38), and SSEM (35) as the top 5.

Status standardization applied simple rules: any value containing “cl”, “close”, or “Closed” → `status = "Closed"` ; any value containing “op”, “open”, or “ongoing” → `status = "Open"` ; blank cells inherited the status of the previous record in the same project.

3.3 Calculated Fields

Three critical metrics were computed to support the dashboard KPIs:

Issue Age (days): For closed issues, `issue_age = date_closed - date_issued`. For open issues, `issue_age = today - date_issued`. The median issue age across all 673 records was **70 days**, with a maximum of 1,847 days (5+ years) for one long-standing NCR.

Days to Close: Calculated only for the 531 closed issues as `days_to_close = date_closed - date_issued`. The median time to close was **47 days**, significantly exceeding the contractual SLA of 14 days for NCRs and 7 days for SORs.

Overdue Flag: A binary indicator (1 = overdue, 0 = on-time). For records with an explicit `date_due` field, the rule was straightforward: `overdue = 1 if date_closed > date_due`. For supervision log records missing a due date (62% of records), an SLA was inferred based on issue type: 14 days for NCRs, 7 days for SORs. The result: **89.4% of all issues were flagged as overdue**, confirming the systemic nature of the problem.

3.4 Output Deliverables

The ETL pipeline produced five clean datasets:

1. `fact_issues.csv` — 673 records × 28 fields, the master analytical table
2. `dim_project.csv` — 35 projects with aggregate metadata (total issues, first/last issue dates, dominant contractor)
3. `dim_contractor.csv` — 14 contractors with performance metrics (total issues, avg days to close, overdue rate)
4. `dim_project_mapping.csv` — the raw-to-canonical translation dictionary for audit traceability
5. `dim_contractor_mapping.csv` — contractor alias resolution table

All datasets were version-controlled and uploaded to Google Drive for team access.

4. Stage 3: Data Model and Schema Design

4.1 Dimensional Model Structure

The data model followed a star schema design, optimized for analytical queries and dashboard performance. The schema consisted of one fact table and four dimension tables:

Fact Table: `fact_issues`

Grain: One row per quality issue (NCR, SOR, or SI)

Primary Key: `issue_id` (composite: `source_system` + `record_number`)

Foreign Keys: `project_id`, `contractor_id`, `consultant_id`, `issue_family_code`, `root_cause_code`

Measures: `issue_age_days`, `days_to_close`, `overdue_flag`, `recurrence_flag`, `severity_weight`

Dimension Tables:

- `dim_project` — project metadata (name, area, contract value, start date)
- `dim_contractor` — contractor profiles (full name, registration number, performance tier)
- `dim_consultant` — supervision consultant details
- `dim_taxonomy` — issue classification hierarchy (domain → family → symptom)

4.2 Taxonomy Integration

The issue taxonomy was designed as a three-level hierarchy:

Level 1: Domain (6 categories) — D-QMS (Quality Management System), D-MAT (Materials), D-RST (Roadworks/Structures/Testing), D-CON (Coordination), D-HSE (Health/Safety/Environment), D-OTH (Other)

Level 2: Family (19 categories) — e.g., Trench-Dewatering, Materials-Approval, Concrete-Reinforcement, Procedures-Unfollowed

Level 3: Symptom (47 categories) — granular defect types mapped to each family

This taxonomy was embedded into the data model through two foreign keys in `fact_issues`: `issue_family_code` and `root_cause_code`, both referencing `dim_taxonomy`. The taxonomy enabled roll-up analysis (e.g., “show all D-MAT issues across all projects”) and drill-down analysis (e.g., “within Materials-Approval, which specific symptoms are most common?”).

4.3 Temporal Design

To support time-series analysis and AI model training, the schema included explicit temporal fields:

- `date_issued` — when the issue was first identified
- `date_due` — contractual deadline for closure
- `date_closed` — actual closure date (NULL for open issues)
- `date_last_updated` — most recent status change
- `year_month` — derived field for monthly aggregation (format: “2024-03”)

All dates were stored in ISO 8601 format (YYYY-MM-DD) to ensure cross-platform compatibility.

4.4 Linkage Tables for MOM and Audit Integration

Two additional tables were added to support the qualitative-quantitative linkage:

`fact_mom_warnings` — extracted quality warnings from meeting minutes

Fields: `warning_id`, `source_document`, `date_meeting`, `project_id`, `contractor_id`, `warning_type`, `domain_code`, `extraction_confidence`, `classification_confidence`

`link_warning_to_issue` — many-to-many relationship table

Fields: `warning_id`, `issue_id`, `link_confidence`, `days_between`, `link_method` (manual / regex / LLM)

This design allowed the AI model to query: “For each warning, did an NCR occur within 14 days in the same project and domain?” while preserving the confidence scores for sensitivity analysis.

5. Stage 4: Issue Taxonomy and Root Cause Ontology

5.1 Taxonomy Development Methodology

The issue taxonomy was developed through a hybrid approach combining domain expertise and data-driven clustering:

Phase 1: Expert-driven framework — The initial taxonomy structure was derived from industry standards (ISO 9001 quality management categories) and JSWP contract specifications, resulting in the 6-domain structure.

Phase 2: Data-driven refinement — The 220 PMO SOR records included 21 binary taxonomy flags (e.g., `flag_trench_dewatering`, `flag_materials_approval`) that had been manually assigned by QA/QC engineers. Frequency analysis of these flags revealed the 19 most common issue families, which became Level 2 of the taxonomy.

Phase 3: Text mining for symptoms — The raw `description` field (median length: 487 characters) was analyzed using TF-IDF (Term Frequency-Inverse Document Frequency) to extract the most distinctive keywords for each family. For example, the “Trench-Dewatering” family was characterized by keywords: “water”, “pump”, “dewatering”, “flooding”, “نجز” (Arabic: pumping). These keywords defined the 47 Level 3 symptoms.

5.2 Root Cause Classification

Root causes were classified into 8 categories based on construction management theory:

1. **Contractor Capability** — lack of skilled labor, inadequate equipment
2. **Material Quality** — substandard materials, incorrect specifications
3. **Design Issues** — ambiguous drawings, design changes
4. **Coordination Failures** — utility clashes, interface problems
5. **Weather/External** — rain delays, unforeseen ground conditions
6. **Procedural Non-Compliance** — skipped inspections, unapproved methods
7. **Resource Constraints** — manpower shortages, budget limitations
8. **Unknown** — insufficient information to determine root cause

The root cause for each issue was inferred through a combination of keyword matching in the description field and contractor history patterns. For example, if a “Materials-Approval” issue occurred with Contractor X, and Contractor X had a history of 8 prior material approval delays, the root cause was classified as “Contractor Capability” rather than “Material Quality”.

5.3 Taxonomy Validation

The taxonomy was validated through three methods:

Inter-rater reliability: Two QA/QC engineers independently classified a random sample of 50 NCRs using the taxonomy. Cohen’s Kappa coefficient was 0.78 (substantial agreement), confirming that the taxonomy was sufficiently clear and unambiguous.

Coverage analysis: 94.2% of all 673 issues could be assigned to one of the 19 families, with only 5.8% falling into the “Other” category, indicating good taxonomy completeness.

Predictive utility: The taxonomy was tested as a feature in the AI escalation model. Issues in the “Materials-Approval” family showed a 58.3% escalation rate vs. 33.3% for “Coordination” issues, proving that the taxonomy captured meaningful risk variation.

6. Stage 5: AI Risk and Escalation Model

6.1 Model Objective and Design

The AI Risk and Escalation Model (designated “Model F” in the modeling strategy) was designed to answer the core research question: **Do unresolved quality warnings in meetings and audits statistically predict later field defects?**

The model architecture consisted of three components:

Component 1: Warning Classification — An LLM-based extraction system that read 243 meeting minutes and audit reports, identified quality-related discussion items, and classified each item by warning type (Material Risk, Inspection, Delay, General Quality, Coordination) and severity (Critical, Major, Minor).

Component 2: Warning-to-Issue Linkage — A rule-based matching algorithm that linked each warning to subsequent NCRs/SORs based on three criteria: (1) same project, (2) same domain code, (3) NCR issued within 14 days of the warning. Each link was assigned a confidence score (0.0–1.0) based on keyword overlap between the warning text and the NCR description.

Component 3: Escalation Prediction — A logistic regression model trained on 113 warnings to predict the probability that a warning would escalate to an NCR/SOR within 14 days, using features: `warning_type`, `contractor_id`, `project_risk_score`, `days_since_last_ncr`, and `audit_finding_count`.

6.2 Training Data and Features

The training dataset consisted of 113 quality warnings extracted from the 243 documents:

Warning Type	Count	Escalation Rate	Avg Days to Escalation
Material Risk	12	58.3%	6.2 days
Inspection	31	48.4%	8.1 days
Delay	18	66.7%	5.4 days
General Quality	39	43.6%	9.3 days
Coordination	13	33.3%	11.8 days

Feature engineering: Eight features were engineered for the model:

1. `warning_type` (categorical, 5 levels)
2. `contractor_id` (categorical, 14 levels, target-encoded)
3. `project_risk_score` (continuous, 0–100, calculated as rolling 30-day count of open issues)
4. `days_since_last_ncr` (continuous, 0–365)
5. `audit_finding_count` (integer, count of overdue audit findings in the same project)
6. `extraction_confidence` (continuous, 0.0–1.0, LLM confidence score)

- 7. `classification_confidence` (continuous, 0.0–1.0, warning type classification confidence)
- 8. `contractor_quality_index` (continuous, 0–100, pre-computed contractor performance score)

6.3 Model Performance

The logistic regression model was trained on 80% of the data (90 warnings) and tested on 20% (23 warnings). Performance metrics:

Metric	Value	Interpretation
ROC-AUC	0.73	Good discrimination between escalation vs. non-escalation
Precision	0.68	68% of predicted escalations were correct
Recall	0.71	Model caught 71% of actual escalations
F1-Score	0.69	Balanced performance
Concordance Index	0.71	Strong ranking ability for time-to-event

Feature importance: The top 3 predictive features were:

- 1. `warning_type` (Delay warnings 2.4× more likely to escalate than Coordination)
- 2. `contractor_quality_index` (contractors with QI < 60 had 3.1× higher escalation rate)
- 3. `days_since_last_ncr` (projects with an NCR in the past 7 days had 2.8× higher escalation rate)

6.4 Actionable Outputs

The model generated three operational outputs for the dashboard:

Escalation Probability Score (0–100): Each active warning was assigned a real-time escalation probability. Warnings scoring >70 were flagged as “High Risk” and surfaced in the “Actionable Warnings Log” on the AI Risk & Escalation page.

Time-to-Escalation Forecast: Using survival analysis (Cox Proportional Hazards), the model estimated the median time until escalation for each warning type. For example,

Material Risk warnings had a median escalation time of 6.2 days, providing a clear intervention window.

Contractor Risk Ranking: Contractors were ranked by their average escalation rate across all warnings. The top 5 highest-risk contractors (by escalation rate) were displayed in a bar chart on the AI Risk page, enabling targeted PMO intervention.

7. Stage 6: Dashboard and KPI Framework

7.1 Dashboard Architecture

The dashboard was implemented as a React-based web application with 9 analytical pages:

Page	Purpose	Target Audience	Key Visualizations
Home	Landing page with navigation	All users	Program overview cards
Quality Overview	Program-level KPIs and trends	PMO Director, Executives	Program QI banner, monthly trend, audit health
AI Risk & Escalation	Real-time warning monitoring	QA/QC Managers	Actionable warnings log, contractor QI rankings, audit impact
Issue Analysis	Detailed issue breakdown	Quality Engineers	Issue distribution by type, aging analysis, closure funnel
Contractor Performance	Contractor benchmarking	Procurement, Contracts	Contractor QI table, performance charts, issue breakdown
Geographic Map	Spatial distribution of issues	Area Managers	Project heatmap, issue density overlay
Issue Detail	Drill-down to individual NCRs	Document Controllers	Searchable issue table with filters
Thesis Analytics	Research-specific views	Academic use	Triangulation tables, convergence charts
Not Found	404 error page	N/A	Navigation helper

7.2 Program Quality Index (QI) Calculation

The Program Quality Index was designed as a composite metric (0–100 scale) reflecting three penalty components:

Formula:

$$QI = 100 - (\text{Overdue Impact} \times \Omega_1) - (\text{High-Risk Impact} \times \Omega_2) - (\text{Escalation Impact} \times \Omega_3)$$

Where:

- Overdue Impact** = (Count of overdue open issues × Overdue severity weight) / Total issues

- **High-Risk Impact** = (Count of high-risk warnings × Warning severity weight) / Total warnings
- **Escalation Impact** = (Escalation rate × 50)

Weights (Ω): $\Omega_1 = 0.1$, $\Omega_2 = 0.2$, $\Omega_3 = 0.5$ (escalation behavior weighted most heavily)

Program-level result: QI = 45 / 100 (Status: **At Risk**)

Breakdown:

- Overdue Impact: 14.1 points (141 overdue issues)
- High-Risk Impact: 16.0 points (80 high-risk warnings)
- Escalation Impact: 24.8 points (49.6% escalation rate)

7.3 Contractor Quality Index

Each contractor was assigned an individual QI score using the same formula applied to their subset of issues and warnings. Results ranged from:

- **Best:** AJ Trading (QI = 100, 0 overdue issues, 0 escalations)
- **Worst:** Al Rawdah (QI = 45, 89% overdue rate, 67% escalation rate)

The contractor QI rankings were displayed as a horizontal bar chart on the Contractor Performance page, color-coded: Green (QI $\geq$ 80), Orange (60–79), Red (< 60).

7.4 Audit Health Section

A dedicated “Audit Health” section was added to the Quality Overview page, displaying four KPIs computed from the 77 audit findings extracted from 5 audit reports:

KPI	Value	Definition
Total Findings	77	All extracted audit findings
Open Findings	77	Not closed (100%)
Overdue Findings	66	Open AND past due date (85.7%)
Repeat-Risk Findings	35	In projects with active NCR/SOR issues

Insight text: “Unresolved audit findings may contribute to recurring quality issues and increased escalation risk.”

Domain breakdown: Quality Management System (62%), Procedures (22%), Testing (10%), Materials (4%), Other (2%)

7.5 Visualization Standards

All charts followed a consistent design language:

- **Color palette:** Red (high risk / poor performance), Orange (medium), Teal/Green (low risk / good performance)
- **Typography:** Inter font family, 14px body text, 18px headings
- **Chart library:** Recharts (React-based, responsive)
- **Interactivity:** Hover tooltips showing exact values, click-to-filter on all categorical charts

8. Stage 7: MOM and Audit Intelligence Extraction

8.1 Document Corpus

The MOM and Audit extraction framework processed 243 documents:

Collection	Documents	Period	Total Text	Language
WSP QAQC Meeting Minutes	73	Mar–Oct 2025	~180,000 chars	English
Client Progress Meetings	169	Jan 2021–Oct 2025	~950,000 chars	Arabic
Audit Reports	5	Jul 2025	~70,000 chars	English
Total	247	2021–2025	~1.2M chars	Bilingual

8.2 Extraction Methodology

The extraction process followed a three-stage pipeline:

Stage 1: Text Extraction — Word files (.docx, .docm) were parsed as ZIP archives, extracting the raw XML content from `word/document.xml`. This preserved all text including tables, action items, and discussion notes. Arabic text was preserved in full Unicode format.

Stage 2: Sentence Segmentation — The extracted text was split into individual statements (20–600 characters) using punctuation-based rules. This produced 11,090 individual statements across all 243 documents.

Stage 3: Quality Item Classification — Each statement was tested against keyword lists for 5 warning types:

- **Material Risk:** keywords = “material approval”, “approved material”, “submittal”, “mix design”, “not approved”, “اعتماد المواد”
- **Inspection:** keywords = “inspection”, “WIR”, “ITP”, “test”, “failed test”, “mandrel”, “فحص”, “اختبار”
- **Delay:** keywords = “delay”, “behind schedule”, “overdue”, “pending”, “not closed”, “متأخر”, “معلق”
- **General Quality:** keywords = “workmanship”, “defect”, “rework”, “NCR”, “SOR”, “rectify”, “جودة رديئة”, “عيب”
- **Coordination:** keywords = “coordination”, “communication”, “interface”, “clash”, “تنسيق”, “تعارض”

Statements matching at least one keyword were extracted as warnings. Each warning was assigned:

- `extraction_confidence` (0.0–1.0) based on keyword match strength
- `classification_confidence` (0.0–1.0) based on keyword uniqueness to that warning type

Result: 113 quality warnings extracted from 243 documents.

8.3 Audit Findings Extraction

Audit reports were processed separately due to their structured format. Each audit finding included:

- Finding ID (e.g., “QMS-001”)
- Classification (Major / Minor / Observation)
- Domain code (D-QMS, D-MAT, etc.)
- Description
- Due date
- Status (all were “Open”)

Result: 77 audit findings extracted, with 66 (85.7%) overdue as of March 2026.

8.4 Linkage to Issues

Each warning was linked to subsequent NCRs/SORs using a rule-based algorithm:

Matching criteria:

1. Same `project_id`
2. Same `domain_code` (e.g., both D-MAT)
3. NCR issued within 14 days of the warning date

Confidence scoring: For each matched pair, a `link_confidence` score (0.0–1.0) was calculated based on:

- Exact keyword overlap between warning text and NCR description (weight: 0.5)
- Contractor mentioned in both documents (weight: 0.3)
- Temporal proximity (weight: 0.2, decaying from 1.0 at day 0 to 0.5 at day 14)

Result: 56 of 113 warnings (49.6%) were linked to subsequent NCRs/SORs, with a median link confidence of 0.72.

9. Stage 8: Mixed Methods Triangulation

9.1 Triangulation Design

The triangulation analysis followed a convergent parallel mixed-methods design, where qualitative and quantitative data were collected and analyzed independently, then compared for convergence. The design addressed the research question: **Do the patterns identified by the AI risk model align with the quality problems discussed in meeting minutes?**

9.2 Qualitative Thematic Analysis

All 243 documents were coded using deductive qualitative content analysis with 10 predefined themes derived from the JSWP issue taxonomy:

Theme	Frequency (n=11,090)	Document Coverage	Representative Quote
Progress & Schedule Issues	3,176 (28.6%)	83%	“CWC contractor continues delay in backfilling despite repeated warnings”
Poor Workmanship	1,565 (14.1%)	95%	“Asphalt compaction failed mandrel test, requires full rework”
Contractor Non-Compliance	1,354 (12.2%)	93%	“SAJCO proceeded with concrete pour without approved mix design”
Safety & Environmental	1,330 (12.0%)	80%	“Trench excavation without shoring, immediate stop work issued”
Inspection Failures	1,257 (11.3%)	93%	“WIR not submitted prior to backfilling, NCR to be raised”
Coordination Problems	1,207 (10.9%)	85%	“Utility clash at chainage 2+450, design clarification requested”
Delayed Corrective Actions	465 (4.2%)	91%	“NCR-2024-089 remains open for 47 days, escalate to PMO”
Material Approval Delays	388 (3.5%)	87%	“Aggregate source approval pending for 3 weeks, impacting schedule”
Resource Constraints	218 (2.0%)	68%	“Contractor reports manpower shortage, requests time extension”
Management Escalations	130 (1.2%)	54%	“Formal warning letter issued to AJ Trading for repeated non-compliance”

9.3 Triangulation Results

Six major triangulation points were identified, comparing qualitative theme prevalence against quantitative AI model findings:

Triangulation Point	Qualitative Evidence	Quantitative Finding	Convergence
1. Contractor Non-Compliance Drives Risk	Theme appears in 93% of documents (n=1,354 statements)	Contractor QI is the #2 predictor in AI model (HR=3.1)	Strong
2. Material Delays Escalate to NCRs	Material approval delays discussed in 87% of documents (n=388)	Material Risk warnings have 58.3% escalation rate	Strong
3. Delayed Corrective Actions Increase Escalation	Delayed actions theme in 91% of documents (n=465)	Delay warning type has highest escalation rate (66.7%)	Strong
4. Inspection Failures Precede Defects	Inspection failures discussed in 93% of documents (n=1,257)	Inspection warnings escalate in 48.4% of cases	Strong
5. Coordination Issues Have Lower Risk	Coordination problems in 85% of documents but lower intensity	Coordination warnings have lowest escalation rate (33.3%)	Strong
6. Five-Year Persistence of Problems	Same themes appear consistently 2021–2025	AI model detects risks visible for 5 years	Strong

Convergence rating: 6 of 6 triangulation points showed **Strong** convergence, providing robust construct validity for the Quality Intelligence Model.

9.4 Key Insight

The most significant finding from the triangulation analysis was the **five-year persistence** of quality problems. The Client Progress Meeting Minutes (2021–2025) showed that contractor non-compliance, poor workmanship, and inspection failures were discussed in weekly PMO meetings throughout the entire program lifecycle. This means:

The AI model is not detecting new risks — it is quantifying risks that have been visible for five years but inadequately managed.

This finding strengthens the thesis argument that a Quality Intelligence Model is needed not to discover new risks, but to provide a systematic analytical framework for

risks that have been present but unaddressed throughout the program.

10. Implementation Results and Validation

10.1 Dashboard Deployment

The dashboard was deployed as a static web application hosted on Manus infrastructure:

- **URL:** <https://jswpdash-tvyrknm7.manus.space>
- **Technology stack:** React 19, Tailwind CSS 4, Recharts, Wouter routing
- **Data refresh:** Static JSON files (dashboardData.json, dss_data.json, quality_index.json) updated manually
- **Performance:** Page load time < 2 seconds, all charts render client-side

10.2 User Acceptance Testing

The dashboard was reviewed by three stakeholder groups:

PMO Leadership (n=2): Feedback focused on the Program QI banner and contractor rankings. Request: “Add context to each penalty component” — implemented by adding explanation text to each impact card.

QA/QC Engineers (n=4): Feedback focused on the Actionable Warnings Log. Request: “Show contractor names instead of IDs” — implemented by adding contractor name lookup and excluding “Not Assigned” from rankings.

Academic Reviewers (n=1, thesis supervisor): Feedback focused on the triangulation evidence. Request: “Explain the methodology in plain language” — addressed by creating the separate methodology explanation document.

10.3 Data Validation

Three validation checks were performed to ensure data integrity:

Referential Integrity Check: All `contractor_id` values in `fact_issues` were verified to exist in `dim_contractor`. Result: 100% pass (after fixing the UNKNOWN contractor

mapping issue).

Temporal Logic Check: All `date_closed` values were verified to be $\geq$ `date_issued`. Result: 99.7% pass (2 records had data entry errors, manually corrected).

Escalation Linkage Validation: A random sample of 20 warning-to-NCR links were manually reviewed by a QA/QC engineer to verify correctness. Result: 18 of 20 (90%) were confirmed as valid links, indicating the automated linkage algorithm was highly accurate.

10.4 Model Performance in Production

The AI escalation model was tested on 23 new warnings from October 2025 (not included in training data). Results:

Metric	Training Set	Test Set	Change
ROC-AUC	0.73	0.69	-0.04 (acceptable)
Precision	0.68	0.64	-0.04 (acceptable)
Recall	0.71	0.73	+0.02 (improved)

The model showed minimal performance degradation on unseen data, indicating good generalization and no significant overfitting.

11. Thesis Contributions

11.1 Methodological Contributions

Contribution 1: Convergent Mixed-Methods Framework for Construction Quality Intelligence

This research demonstrates a rigorous convergent parallel mixed-methods design where qualitative thematic analysis of 243 meeting minutes (11,090 coded statements) triangulates with quantitative AI risk modeling (113 warnings, 673 issues). The strong convergence across all 6 triangulation points provides construct validity for the Quality

Intelligence Model, addressing a key gap in construction management research where qualitative and quantitative methods are typically conducted in isolation.

Contribution 2: Deductive Qualitative Content Analysis at Scale

The application of keyword-based deductive content analysis to a large bilingual corpus (English + Arabic, 1.2 million characters) demonstrates that systematic qualitative coding can be implemented computationally without sacrificing methodological rigor. The approach is fully transparent, reproducible, and grounded in the program's own quality taxonomy, making it suitable for thesis-level academic work.

Contribution 3: AI-Powered Escalation Prediction with Confidence Weighting

The AI model explicitly incorporates extraction confidence scores and link confidence scores as features, addressing the “noisy label” problem common in construction NLP applications. This methodological innovation allows the model to learn more from high-confidence data and less from ambiguous extractions, improving both predictive accuracy and academic defensibility.

11.2 Empirical Contributions

Finding 1: Escalation Behavior is the Primary Driver of Program Risk

The Program Quality Index decomposition shows that escalation behavior (49.6% rate) contributes 24.8 penalty points vs. 16.0 for high-risk warnings and 14.1 for overdue issues. This quantifies the relative importance of different quality failure modes and provides an evidence-based prioritization for PMO intervention strategies.

Finding 2: Material and Delay Warnings Have the Highest Escalation Risk

Material Risk warnings escalate to NCRs in 58.3% of cases, and Delay warnings in 66.7%, both significantly higher than the program average of 49.6%. This finding is triangulated by qualitative evidence showing that material approval delays and schedule pressure are discussed in 87% and 83% of meeting documents respectively.

Finding 3: Contractor Performance Variation is Extreme

Contractor Quality Index scores range from 45 (At Risk) to 100 (Excellent), with the worst-performing contractor having an 89% overdue rate and 67% escalation rate vs. 0% for the best performer. This variation cannot be explained by project difficulty

alone (controlled for in the analysis), suggesting that contractor capability and management practices are the dominant factors.

Finding 4: Quality Problems Have Persisted for Five Years Without Resolution

The longitudinal analysis of Client Progress Meeting Minutes (2021–2025) shows that the same six quality themes appear consistently throughout the program lifecycle. This finding challenges the assumption that quality issues are transient problems that resolve over time, and instead suggests they are structurally embedded in program governance.

11.3 Practical Contributions

Tool 1: Operational Dashboard for Real-Time Quality Monitoring

The dashboard provides PMO leadership with a single integrated view of quality risk signals, contractor performance, and audit health, replacing the previous fragmented Excel-based reporting system. Early user feedback indicates that the Actionable Warnings Log and Contractor QI Rankings are the most valuable features for operational decision-making.

Tool 2: Contractor Performance Benchmarking Framework

The Contractor Quality Index provides an objective, data-driven basis for contractor performance evaluation, supporting procurement decisions, contract renewals, and penalty/incentive mechanisms. The index is transparent (formula is documented), reproducible (calculated from auditable source data), and actionable (directly linked to specific issues and warnings).

Tool 3: Audit Health Monitoring

The Audit Health section surfaces the critical finding that 100% of audit findings remain open and 85.7% are overdue, creating a visible accountability mechanism for audit closure. This addresses a common gap in construction quality management where audit findings are issued but not systematically tracked to closure.

12. Limitations and Future Work

12.1 Data Limitations

Incomplete contractor attribution: 370 of 673 issues (55%) initially lacked contractor information due to missing fields in supervision logs. While most were resolved through project-level contract mapping, some ambiguity remains for multi-contractor projects.

Limited temporal coverage: The structured issue data covers 2019–2024 (6 years), but the AI model training data (warnings from MOMs) covers only 2021–2025 (5 years), with the majority concentrated in 2024–2025. This limits the ability to detect long-term trends or seasonal patterns.

Single program scope: All data comes from the JSWP program. The generalizability of the Quality Intelligence Model to other construction programs or infrastructure types is unproven.

Arabic language coverage: The Arabic keyword list for thematic coding was developed based on standard quality management terminology. Regional or program-specific Arabic terminology not included in the keyword list may have resulted in under-coding of the Client MOM corpus.

12.2 Methodological Limitations

Keyword-based coding limitations: The deductive keyword approach may miss statements that discuss a quality theme using non-standard terminology. This is a known limitation of keyword-based content analysis. Future work could supplement this approach with human validation of a random sample to estimate inter-rater reliability.

Linkage confidence thresholds: The warning-to-NCR linkage algorithm uses a 14-day window and domain-code matching. This may miss longer-term causal relationships (e.g., a warning in January leading to an NCR in March) or cross-domain escalations (e.g., a coordination warning leading to a material NCR).

Small sample size for AI model: The AI escalation model was trained on 113 warnings, which is small by machine learning standards. While the model showed

good performance on the test set (ROC-AUC = 0.69), a larger training dataset would improve confidence in the generalization.

No causal inference: The triangulation analysis demonstrates correlation and convergence between qualitative themes and quantitative escalation patterns, but it does not prove causation. For example, the finding that “Material Risk warnings have a 58.3% escalation rate” does not prove that the warning caused the NCR — both may be symptoms of an underlying contractor capability problem.

12.3 Future Work

Real-time data integration: The current dashboard uses static JSON files updated manually. Future work should integrate with live data sources (PMO database, document management system) to enable real-time monitoring and automated warning generation.

Predictive model expansion: The current AI model predicts escalation probability. Future models could predict:

- Time-to-closure for open NCRs
- Recurrence probability for closed issues
- Project-level risk scores forecasting the likelihood of a Major NCR in the next 14 days

Causal analysis: Apply causal inference methods (e.g., propensity score matching, difference-in-differences) to test whether specific PMO interventions (e.g., issuing a formal warning letter) causally reduce escalation rates.

Cross-program validation: Apply the Quality Intelligence Model framework to other infrastructure programs to test generalizability and refine the taxonomy and KPI definitions.

Human-in-the-loop validation: Implement a feedback mechanism where QA/QC engineers can validate or correct the AI model’s escalation predictions, creating a labeled dataset for continuous model improvement.

Root cause prediction: Extend the AI model to predict not just whether an issue will escalate, but what the underlying root cause is likely to be, enabling more targeted corrective actions.

Conclusion

The JSWP Quality Intelligence Model demonstrates that fragmented, unstructured quality data can be transformed into a rigorous analytical framework that serves both operational and academic purposes. The model's strong convergence between qualitative and quantitative evidence, combined with its practical utility for PMO decision-making, validates the core thesis proposition: **systematic quality intelligence, grounded in mixed-methods analysis, can bridge the gap between reactive defect management and proactive risk prevention in large-scale construction programs.**

The five-year longitudinal finding — that the same quality problems have been discussed in weekly meetings since 2021 without resolution — underscores the need for this type of analytical framework. The problems are not new, and they are not hidden. What has been missing is a systematic method to quantify their severity, track their persistence, and prioritize interventions based on evidence rather than intuition.

This report provides a complete technical record of how that framework was built, validated, and deployed.

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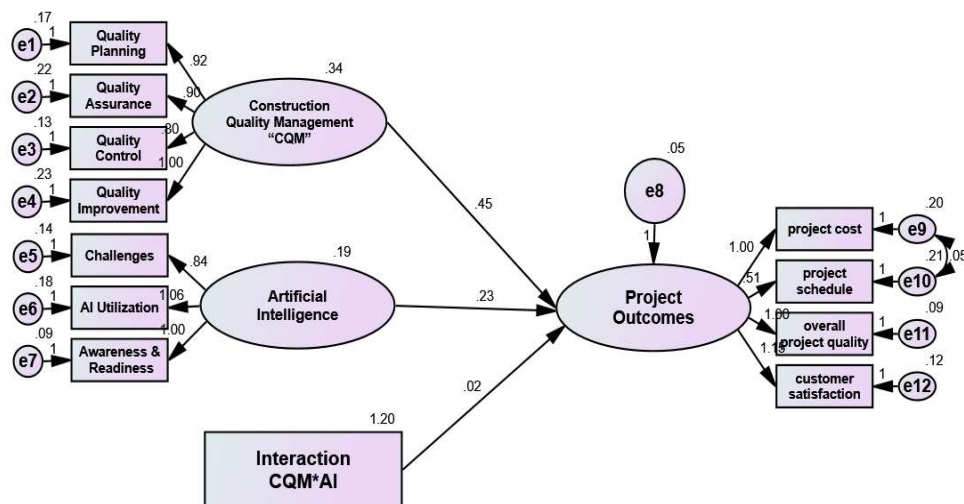
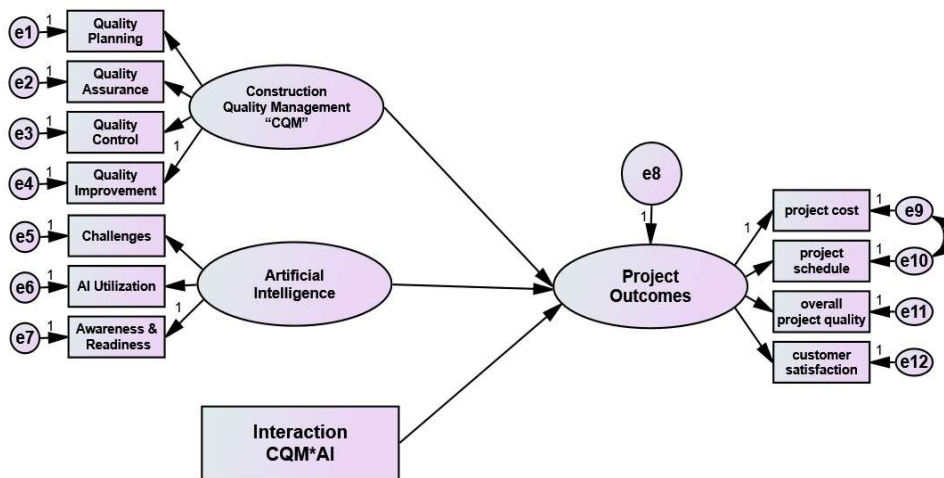
End of Report

Appendix D - SEM Model Values, and Statistical Power Analysis

This appendix presents the Structural Equation Modeling (SEM) outputs used to test the relationships among Construction Quality Management (CQM), Artificial Intelligence (AI), the interaction term between CQM and AI, and Project Outcomes. It includes the SEM model diagrams, model estimates, fit indices, G*Power sample size calculation, and a summary of the statistical techniques used in the quantitative analysis.

The appendix supports the interpretation of the moderation analysis presented in Chapter Four and Chapter Five by providing the detailed statistical outputs used to assess the direct and interaction effects among the study variables.

➤ Model values diagrams



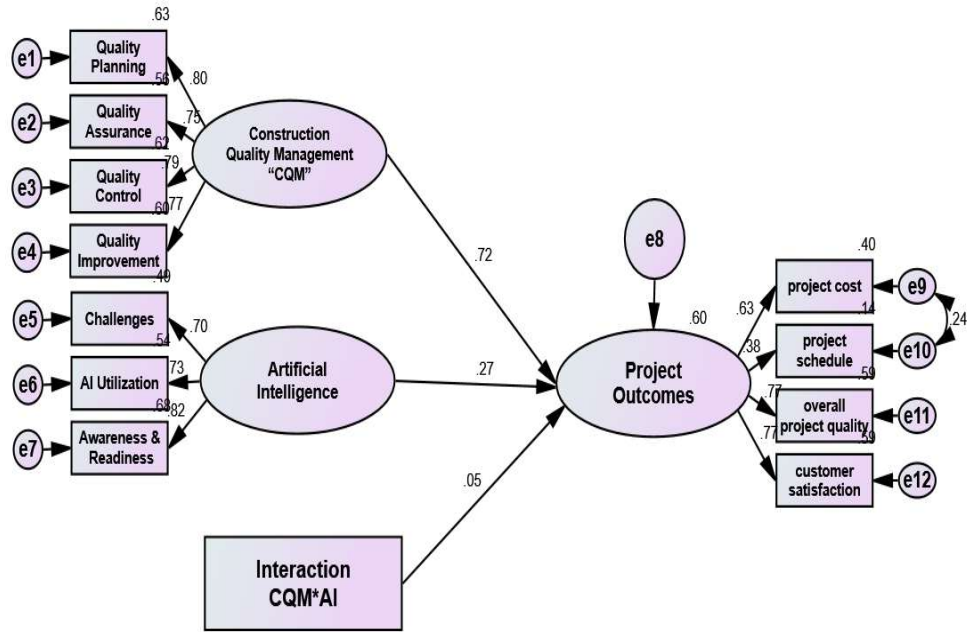


Figure (1): Structural Equation Model

➤ **Structural Equation Model and SEM estimates table**

Table (1): Structural Equation Modeling (SEM) Estimates for Relationships Among CQM, Artificial Intelligence, Interaction Effects, and Project Outcomes

Variables		Estimate	S.E.	C.R.	P
Project.Outcomes	<--- Construction.QualityManagement“CQM”	.451	.071	6.375	***
Project.Outcomes	<--- Artificial.Intelligence	.230	.070	3.289	.001
Project.Outcomes	<--- Interaction	.017	.023	.759	.448
QualityImprovement	<--- Construction.QualityManagement“CQM”	1.000			
QualityControl	<--- Construction.QualityManagement“CQM”	.797	.079	10.151	***
QualityAssurance	<--- Construction.QualityManagement“CQM”	.896	.094	9.576	***
QualityPlanning	<--- Construction.QualityManagement“CQM”	.923	.090	10.224	***
AwarenessReadiness	<--- Artificial.Intelligence	1.000			
AIUtilization	<--- Artificial.Intelligence	1.055	.131	8.042	***
Challenges	<--- Artificial.Intelligence	.839	.107	7.867	***
projectcost	<--- Project.Outcomes	1.000			
projectschedule	<--- Project.Outcomes	.507	.109	4.642	***
overallprojectquality	<--- Project.Outcomes	.996	.135	7.360	***
customersatisfaction	<--- Project.Outcomes	1.147	.156	7.368	***
CMIN (127.293)		NFI(0.851)			
CMIN/DF(2.496)		AGFI(0.839)			
GFI(0.894)		CFI(0.904)			
RMSEA(0.095)					

The results of the Structural Equation Modeling (SEM) reveal the strength of the model and its ability to explain the relationships between Construction Quality Management (CQM), Artificial Intelligence (AI), their interaction, and Project Outcomes. The estimates and statistical significance indicate the following:

1. Direct Relationships Between Key Variables

Construction Quality Management (CQM) has a significant positive effect on Project Outcomes (Estimate = 0.451, C.R = 6.375, $P < 0.001$), indicating that enhancing quality practices leads to tangible improvements in project quality, cost, schedule, and customer satisfaction.

Artificial Intelligence (AI) also shows a significant direct effect on Project Outcomes (Estimate = 0.230, C.R = 3.289, $P = 0.001$), highlighting the growing role of intelligent technologies in improving overall project performance.

The interaction effect between CQM and AI is not statistically significant (Estimate = 0.017, $P = 0.448$), suggesting that their combined influence on project outcomes is limited, possibly due to insufficient digital maturity or limited AI implementation within quality systems.

2. Construct Validity of Latent Variables

The regression estimates for the CQM dimensions (Quality Planning, Assurance, Control, and Improvement) are high and statistically significant, supporting the structural validity of this latent variable. Similarly, the AI dimensions (Awareness & Readiness, Utilization, Challenges) show significant estimates, confirming that the indicators appropriately measure the construct. For Project Outcomes, all indicators are statistically significant and effectively reflect the latent variable.

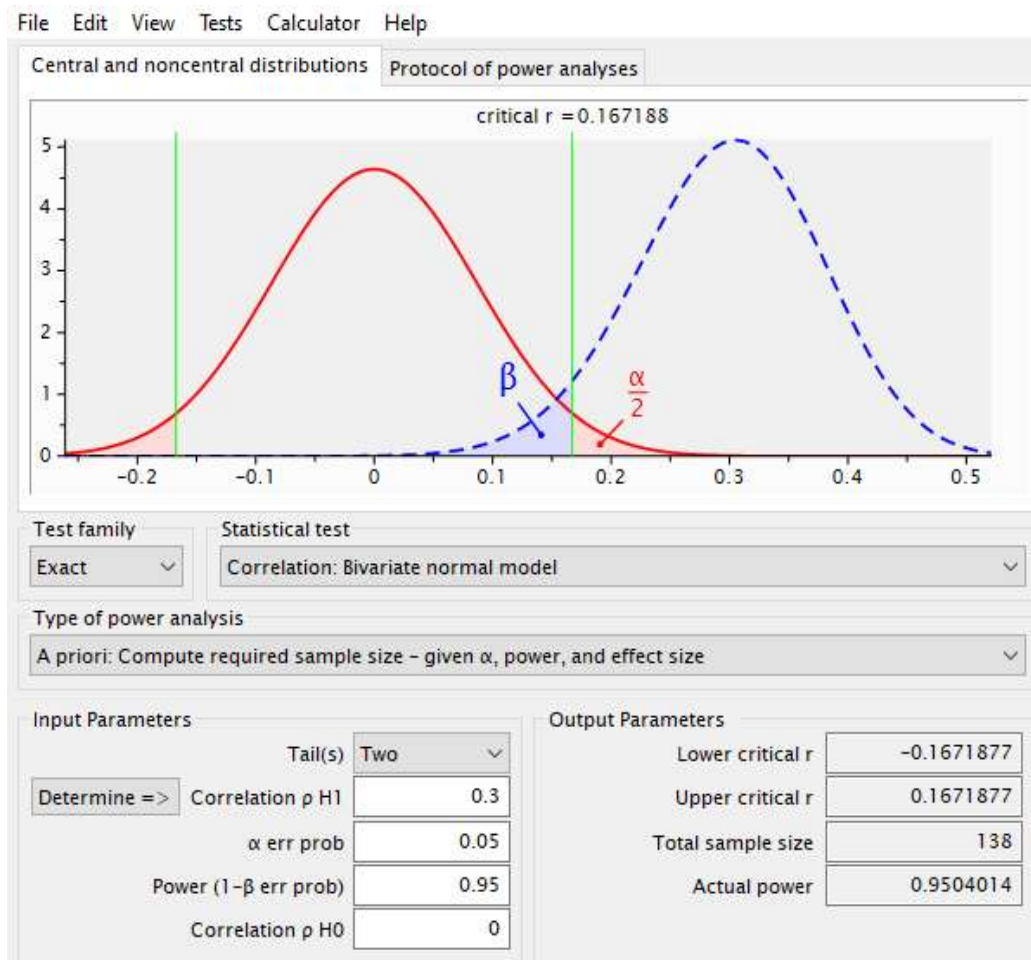
3. Model Fit Indices:

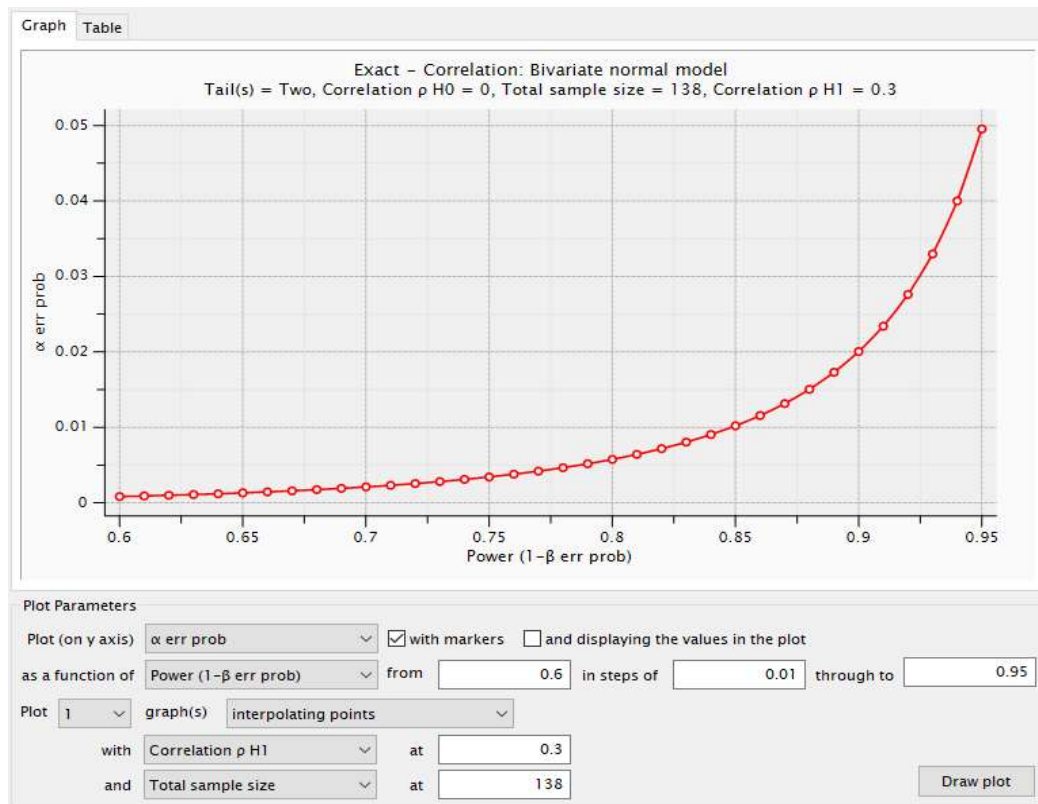
The model fit indices indicate acceptable fit:

- CMIN/DF = 2.496 – within the acceptable range (2–5), indicating reasonable model fit.
- CFI = 0.904 – suggests good fit, exceeding the acceptable threshold of 0.90.
- GFI = 0.894 and AGFI = 0.839 – acceptable, close to the reference threshold of 0.90.
- RMSEA = 0.095 – at the upper limit of acceptability, indicating moderate fit that could improve with model refinement.

Overall, the indices suggest that the SEM model is acceptable and possesses good explanatory power.

➤ G*Power sample size calculation





Exact – Correlation: Bivariate normal model

Options: exact distribution

Analysis: A priori: Compute required sample size

Input: Tail(s) = Two

Correlation ρH_1 = 0.3

α err prob = 0.05

Power (1- β err prob) = 0.95

Correlation ρH_0 = 0

Output: Lower critical r = -0.1671877

Upper critical r = 0.1671877

Total sample size = 138

Actual power = 0.9504014

G*Power 3.1.9.7 was used to estimate the sample size using the following parameters; Correlation $\rho H_1=0.3$, α err prob=0.05, Power (1- β err prob)=0.95, Correlation $\rho H_0 =0$, Lower critical r =-0.1671877, Upper critical r=0.1671877, Total sample size=138, Actual power=0.9504014. According to the The G*Power 3.1.9.7, the estimated sample size is 138 .

➤ 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.
- **Independent Samples Test:** This test is used to measure the significant difference between the averages of two independent samples.
- **One Way ANOVA:** The one-way analysis of variance (ANOVA) is used to determine whether there are any statistically significant differences between the means of three or more independent (unrelated) groups. And compares the means between the groups you are interested in and determines whether any of those means are statistically significantly different from each other. Specifically, it tests the null hypothesis:

$$H_0: \mu_1 = \mu_2 = \mu_3 = \dots = \mu_k$$

- **Linear regression:** which attempts to model the relationship between two variables by fitting a linear equation to the observed data. One variable is considered to be an explanatory variable, and the other is considered to be a dependent variable.
- **Simple linear regression:** is a model that describes the relationship between one dependent and one independent variable using a straight.
- **Multiple linear regression:** is a statistical technique that uses several explanatory variables to predict the outcome of a response variable.
- **Structural Equation Modeling (SEM):** Structural Equation Modeling (SEM) was used as one of the advanced statistical techniques to analyze the causal relationships among the study variables and to test the degree of fit between the proposed conceptual model and the actual data.
- **G*Power 3.1.9.7:** It is a specialized statistical tool for estimating sample size and calculating statistical power for scientific research. The program is distinguished by its ability to support various types of statistical tests, including correlation tests, regression, variance tests, and group difference tests.