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OPTIMIZING QUALITY MANAGEMENT IN THE CONSTRUCTION INDUSTRY: A COQ-BASED PREDICTIVE ANALYSIS

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ABSTRACT

The construction industry faces persistent challenges due to the absence of a standardized financial classification system for quality-related costs, resulting in inefficiencies and project delays. The Cost of Quality (COQ) framework, widely utilized in manufacturing, remains underutilized in construction due to its static assumptions that fail to account for complex interdependencies among quality costs. This study refines COQ classifications and examines the relationship between visible factors (VF) and hidden factors (HF) by using a predictive approach. To fill this gap, a questionnaire survey of 142 construction quality professionals in India was analyzed using SmartPLS 4.0, leading to the development of a predictive COQ model. The Partial Least Squares Structural Equation Modelling (PLS-SEM) results reveal that prevention costs significantly reduce external failure costs ($\beta = 0.465$, $p < 0.05$), while other hypothesized paths, including internal to external failure, were not statistically significant. The model explains 13.2%–22.0% of the variance across COQ components. These findings suggest that prioritizing preventive measures, particularly strategic planning and quality data analysis, is crucial for cost optimization in construction. The study contributes a validated predictive framework and highlights avenues for future research, including regional COQ indexes and AI-enhanced quality monitoring.

Keywords: *Complexity Theory; Construction Industry; Cost of Quality; Predictive Model; SmartPLS.*

1. INTRODUCTION

Quality issues in construction projects are a major concern, frequently leading to disputes between clients and contractors due to defects and inconsistent quality standards (Jha & Chockalingam, 2009). Studies indicate that poor quality in construction results in significant project delays, costly rework, and reduced overall efficiency (Kazaz & Birgonul, 2005). One of the key factors contributing to these challenges is the lack of uniformity in defining and measuring quality. In construction, quality is often defined as "fitness for use," while in other industries, it is characterized as "meeting customer expectations." This inconsistency in definitions can lead to subjective assessments and financial inefficiencies.

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The emergence of Quality 4.0, which integrates digital tools and smart technologies to improve quality management, presents a new opportunity to enhance quality frameworks in construction. Traditional Quality Management (QM) approaches, such as Total Quality Management (TQM), International Organization for Standardization (ISO) standards, and Six Sigma, have been widely used to improve quality performance (Sharma & Laishram, 2024). These approaches have led to better communication, reduced material wastage, and fewer instances of rework. However, despite their benefits, the construction industry continues to struggle with accuracy in quality standards, leading to non-transparent decision-making and cost inefficiencies (Hall & Tomkins, 2001). Many construction firms also underestimate the actual expenses linked to poor quality, affecting their overall profitability. The manufacturing sector, in contrast, has successfully demonstrated how effective quality management can drive profitability and establish consistent quality standards through the Cost of Quality (COQ) framework (Pursglove, 1995). COQ analysis enables organizations to set quality objectives, evaluate system efficiency, and develop strategic decisions. While COQ has proven effective in quantifying and improving quality management in manufacturing, its application in construction remains limited. A significant reason for this underutilization is the reliance on traditional accounting systems, which often fail to align with COQ measurement needs. As a result, many construction firms overlook the financial benefits of proactive quality management, leading to higher failure costs and reactive quality control measures (Garg & Misra, 2021). A key limitation of the traditional COQ framework is its static nature, which assumes fixed relationships between cost components (Kazaz et al., 2005). In reality, quality-related costs interact dynamically as organizations enhance their quality processes; the costs associated with prevention and appraisal fluctuate, influencing failure costs over time. The traditional COQ model does not account for these adaptive changes, leading to gaps in decision-making. To address these issues, there is a need for a more dynamic COQ framework that incorporates complex interactions and feedback mechanisms within quality management systems. This study introduces a new perspective on COQ, modelling dynamic interactions between cost components and incorporating Visible Factors (VF) and Hidden Factors (HF). By leveraging complexity theory, this research proposes a more adaptable COQ model that reflects real-world quality cost variations in construction. To bridge the theoretical and practical gaps in COQ applications within the construction industry, this study sets out to achieve three key objectives: (i) to investigate the dynamic interrelationships among the four COQ categories such as prevention, appraisal, internal failure, and external failure costs; (ii) to evaluate the influence of visible and hidden factors on quality cost performance; and (iii) to construct and validate a predictive model using Partial Least Squares Structural Equation Modelling (PLS-SEM). By contextualizing these objectives within construction project environments and applying complexity theory, the study provides new insights into how strategic quality investments can lead to improved cost efficiency and decision-making.

2. LITERATURE REVIEW

2.1 CONCEPT OF COST OF QUALITY

The COQ framework was first introduced by Juran and Godfrey (1951) in their book Quality Control Handbook. They defined COQ as the total cost incurred due to quality-related issues, emphasizing that these costs could be eliminated if no quality problems existed. Similarly, Crosby (1979) described COQ as a key performance indicator, stating that reducing quality-related costs leads to improved overall performance. This perspective highlights COQ as a critical tool for translating quality efforts into financial metrics, making it more accessible to decision-makers and project managers in construction.

The COQ framework is classified into four key categories, based on BS 6143: Part 2 (1990):

1. Prevention costs – Investments made to ensure consistent quality performance through employee training, system improvements, and defect prevention (Hall & Tomkins, 2001).
2. Appraisal costs – Expenses allocated to inspections, audits, and monitoring to maintain quality compliance (Hall & Tomkins, 2001; Heravi & Jafari, 2014).
3. Internal failure costs – Costs associated with errors detected before project completion, such as rework, redesigns, and defective material replacements (Hall & Tomkins, 2001; Heravi & Jafari, 2014).
4. External failure costs – Expenses incurred after project delivery, including legal disputes, warranty claims, and reputational damage (Hall & Tomkins, 2001).

Most research on COQ in construction has focused on examining relationships between these cost categories. Some studies suggest that failure costs tend to be lower in well-managed projects, where prevention and appraisal investments play a crucial role in minimizing quality issues. However, other studies challenge this assumption, arguing that COQ relationships are complex and influenced by various internal and external factors.

2.2 RESEARCH GAP

Despite the growing interest in applying COQ frameworks across industries, existing research has largely focused on manufacturing, leaving a gap in understanding its relevance to construction. Unlike manufacturing, construction projects are highly dynamic, involve multiple stakeholders, and suffer from inconsistent quality standards and documentation (Hall & Tomkins, 2001; Kazaz & Birgonul, 2005). Traditional COQ models are ill-equipped to account for these complexities. Moreover, few studies have explicitly explored how HF interact with measurable quality costs (Khadim et al., 2023). By integrating complexity theory and PLS-SEM, this study hypothesizes that prevention investments and professional roles are not only drivers of COQ efficiency but also act through dynamic relationships that differ by project context. This theoretical framing strengthens the model’s relevance to construction and provides a foundation for its predictive hypotheses. By developing a predictive COQ model, this research aims to enhance decision-making in construction quality management and provide practical recommendations for industry professionals. A strategic roadmap has been developed to address the limitations of the traditional COQ model and facilitate the adoption of a predictive quality cost framework in the construction industry. This approach explores the interrelationships among COQ components through a structured hypothesis-driven analysis:

- H1: There is a significant relationship between prevention costs and internal failure costs, where increased appraisal efforts contribute to reducing internal failure costs.

- H2: Internal failure costs are positively correlated with external failure costs, meaning that higher internal failure costs are associated with greater external failure costs.
- H3: There is a significant positive relationship between prevention costs and external failure costs, indicating that increased prevention efforts lead to a reduction in external failure costs.
- H4: Stakeholder involvement plays a critical role in optimizing COQ, suggesting that effective engagement and collaboration contribute to achieving cost efficiency and quality improvements.

3. METHODOLOGY

This study adopted a comprehensive four-stage research strategy to explore the influence of VF and HF on the COQ in construction projects. The methodology was designed to ensure a systematic and structured approach to addressing the research objectives through literature review, expert validation, data collection, statistical analysis, and model development. The first stage involved an extensive literature review to identify key factors influencing COQ in construction. A desktop search using Scopus, Web of Science (WOS), and EBSCOhost was conducted, employing the building blocks approach for keyword identification (Araújo et al., 2017). The search included keywords such as "cost of quality," "quality costs," "construction industry," "quality models," "rework," and "PAF" to filter relevant studies. The snowballing and trial-and-error techniques further refined the selection process, leading to the identification of 22 critical factors, which were subsequently grouped into visible and hidden categories. The second stage involved the administration of a self-administered questionnaire to examine the impact of VF and HF on COQ components. This approach, widely recognized in construction management research, enabled the collection of responses from a diverse and geographically dispersed sample (Raouf & Ghamdi, 2020). A pilot study with five participants was initially conducted to assess the clarity and reliability of the questionnaire, leading to refinements before full-scale distribution. The final survey, developed using Google Forms, consisted of two sections: one covering demographic information and the other assessing 22 COQ-related factors on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The sample size was determined using Cochran's formula, establishing a minimum requirement of 97 respondents for a 95% confidence level (Heravi & Jafari, 2014). The study successfully collected 142 valid responses, ensuring statistical robustness. A purposive sampling strategy was employed to target professionals actively involved in construction quality management, allowing for a focused examination of COQ practices (Palinkas et al., 2015). The third stage comprised data analysis, conducted using Statistical Package for Social Sciences (SPSS) version 29. Various statistical techniques were employed to validate the data and identify key relationships:

- Reliability Analysis: Cronbach's alpha was used to assess internal consistency, yielding a coefficient of 0.847, exceeding the recommended threshold of 0.7 (Hoque & Hasan, 2022).
- Normality Testing: The Kolmogorov-Smirnov (K-S) test and z-scores for skewness and kurtosis confirmed a non-normal distribution, justifying the use of non-parametric methods.

- Non-Parametric Tests: The Kruskal-Wallis test and Post-hoc analysis identified statistically significant differences among COQ categories, aligning with the ordinal nature of the data (Chan & Tam, 2000).

The fourth stage involved the construction and evaluation of a hypothetical predictive model. The proposed model comprises five latent constructs: prevention cost, appraisal cost, internal failure cost, and external failure cost. Additionally, a fifth construct, quality professional role, was incorporated to evaluate moderating effects. An initial conceptual framework was formulated on the basis of theoretical relationships (H1–H4). This model was tested using PLS-SEM via SmartPLS 4.0. PLS-SEM was selected due to its ability to handle complex models with latent variables, making it ideal for this exploratory study (Hair et al., 2014). Figure 1 and Table 5 presents the refined model, which reflects the removal of statistically insignificant paths and highlights significant influences along with the model's explanatory power. The model's reliability was assessed through Composite Reliability (CR), Cronbach's Alpha (α), and Average Variance Extracted (AVE). The results showed that all AVE values exceeded 0.5, confirming strong construct validity (Fornell & Larcker, 1981). Additionally, bootstrapping with 5000 resamples was performed to establish confidence intervals for path coefficients, ensuring statistical robustness (Ghani et al., 2017). This four-stage methodology provides a comprehensive framework for analyzing COQ in construction projects, integrating expert insights, advanced statistical techniques, and robust modelling approaches. The combination of qualitative expert validation, quantitative data analysis, and PLS-SEM modelling enhances the practical application of COQ strategies and contributes to the ongoing discourse on quality management in the construction industry.

4. DATA ANALYSIS

The collected data was analyzed using SPSS version 29 and SmartPLS 4.0 to assess the relationships between COQ components and the influence of VF and HF.

4.1 RELIABILITY AND VALIDITY ANALYSIS

To ensure internal consistency, Cronbach's Alpha (α) was used, achieving a reliability score of 0.847, surpassing the minimum threshold of 0.7. Moreover, CR further confirmed the robustness of the measurement model, while AVE ensured that each construct effectively captured the intended variance.

4.2 NORMALITY TESTING AND NON-PARAMETRIC ANALYSIS

Data normality was assessed using the Kolmogorov-Smirnov (K-S) test, which indicated deviations from normal distribution. Consequently, non-parametric tests were applied. The Kruskal-Wallis test examined differences across respondent groups, while Post-hoc analysis identified specific variations among COQ categories.

4.3 PARTIAL LEAST SQUARE-STRUCTURAL EQUATION MODELLING (PLS-SEM)

4.3.1 Model Development

A predictive model was formulated based on insights drawn from the literature review and findings from non-parametric tests. Through an iterative refinement process, factors with low path coefficients were systematically removed to enhance model consistency.

The finalized PLS-SEM model was assessed using reliability and validity tests, ensuring its robustness, as depicted in Figure 1. To verify construct reliability, key statistical measures including Cronbach's Alpha, CR, and AVE, were derived from SmartPLS 4.0. The results confirmed acceptable convergent validity across all constructs, as summarized in Table 1. Additionally, discriminant validity was evaluated using the Fornell-Larcker criterion and cross-loading assessments. The Fornell-Larcker criterion requires that the square root of AVE for each construct be greater than its correlation with other latent variables, a condition met in this study, as detailed in Table 2. Furthermore, cross-loading assessments confirmed that each indicator exhibited higher loadings with its own construct than with unrelated variables, meeting the validity requirements outlined in Table 3.

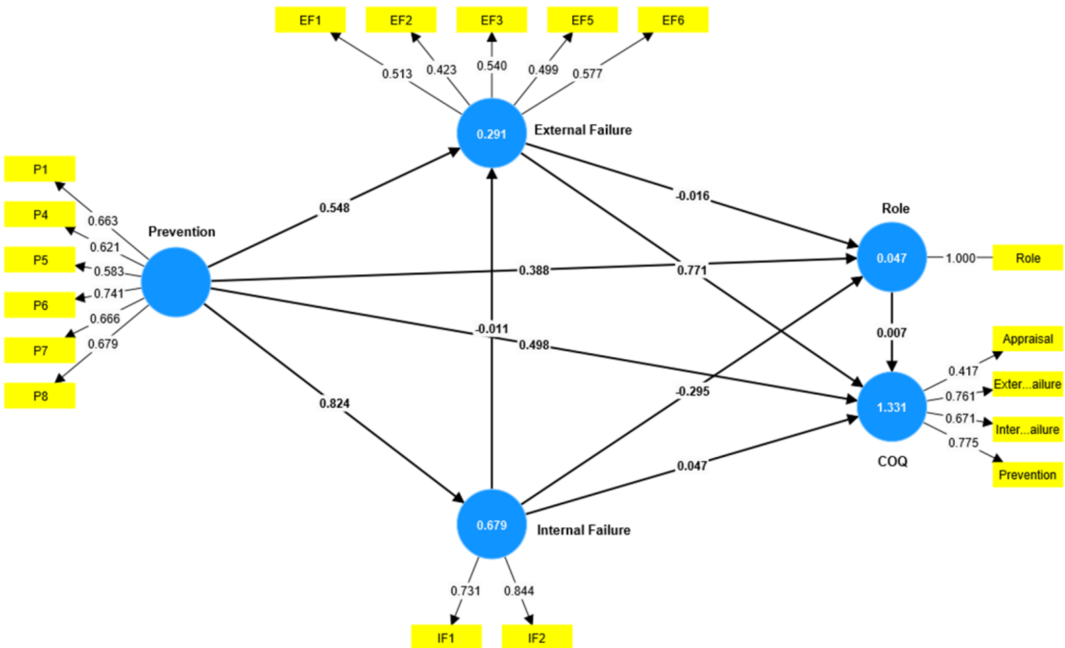

Figure 1: Final model

Table 1: Results of reliability tests

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
COQ	0.765	0.788	0.758	0.451
External Failure	0.637	0.644	0.639	0.263
Internal Failure	0.763	0.774	0.767	0.623
Prevention	0.819	0.825	0.822	0.436

Table 2: Results of Fornell-Larcker criterion

Constructs	COQ	External failure	Internal failure	Prevention	Role
COQ	0.672				
External Failure	1.061	0.513			
Internal Failure	0.797	0.441	0.789		

Constructs	COQ	External failure	Internal failure	Prevention	Role
Prevention	0.953	0.539	0.824	0.660	

4.3.2 Model Evaluation

Following the verification of reliability and validity, the model's explanatory power and path coefficients were assessed. The R-squared (R^2) values indicated the proportion of variance explained by the model, with values of 22.0% for Prevention, 21.0% for Internal Failure, and 13.2% for External Failure, demonstrating a substantial explanatory capacity for these categories. The significance of the path coefficients (denoted as ß1 to ß2) was tested using bootstrapping with 5000 resamples in SmartPLS 4.0. The bootstrapping method involves resampling the dataset multiple times and rerunning the PLS model to ensure result consistency. The statistical reliability of the dataset, alongside observed path coefficients (p-values and outer weights at the 95% confidence interval), was verified using this methodology. The analysis revealed that two hypotheses attained statistical significance, whereas three hypotheses did not, as summarized in Table 4. However, all hypothesized relationships exhibited a positive directional influence, reinforcing the interconnectivity of COQ components in construction quality management.

Table 3: Results of cross-loading of PLS model

Items	COQ	External failure	Internal failure	Prevention	Role
EF1 (Complaints)	0.480	0.550	0.190	0.256	0.065
EF2 (Liability claims)	0.394	0.538	0.183	0.226	-0.073
EF3 (Penalties for poor quality)	0.515	0.691	0.165	0.254	0.091
EF5 (Costs of repair during warranty period)	0.478	0.716	0.190	0.232	0.009
EF6 (Delay of Project)	0.537	0.692	0.262	0.285	0.048
IF1 (Rejected item)	0.525	0.315	0.883	0.513	0.044
IF2 (Repair, rework, or replacement)	0.591	0.250	0.914	0.662	-0.012
P1 (Strategic planning for COQ)	0.566	0.216	0.522	0.766	0.064
P4 (Maintenance & Calibration of test and measuring equipment)	0.530	0.318	0.400	0.630	0.171
P5 (Assuring contractor/supplier/sub-contractor quality)	0.477	0.183	0.478	0.631	0.112
P6 (Staff training)	0.639	0.320	0.541	0.794	0.009
P7 (Acquisition, analysis & reporting of quality data)	0.556	0.327	0.466	0.751	0.100
P8 (Quality improvement programs)	0.575	0.340	0.462	0.775	0.104

5. RESULTS

The findings of this study provide insights into the influence of professional roles, VF and HF factors, and COQ categories on quality cost dynamics in the construction industry. The analysis highlights key relationships that impact COQ optimization and cost management strategies. The Kruskal-Wallis test results indicate that a respondent's profession does not significantly impact their expertise in COQ components, including prevention, appraisal, internal failure, and external failure costs. Post-hoc analysis further supports this, with p-values above 0.05 across all categories. Despite the lack of significant variance in expertise levels, the role of quality professionals in construction remains vital for minimizing quality-related costs by ensuring the effective implementation of standards and processes. Their expertise helps mitigate defects, reduce rework, and improve cost efficiency. However, studies suggest that top management commitment is a critical determinant of COQ success (Aoieong et al., 2002). Organizations that prioritize structured quality investments through training, process optimization, and advanced quality management (QM) systems achieve greater cost reductions in the long term (Mashwama et al., 2017). Conversely, when management focuses solely on cost-cutting rather than quality improvements, higher failure costs arise due to rework, client dissatisfaction, legal disputes, and warranty claims (Omar & Murgan, 2014). A collaborative approach between top management and quality professionals is therefore essential for enhancing COQ efficiency and cost savings.

The study also highlights the significance of VF and HF in COQ performance. Among HF, the most critical factors include strategic planning for COQ (P1) and quality data analysis (P7), both of which play a major role in long-term cost efficiency. Organizations investing in staff training and quality improvement programs experience immediate improvements in defect reduction and cost control. Research suggests that at least 30 hours of quality training significantly improves workforce performance, while extending training to 100 hours correlates with increased labour productivity (Shafiei et al., 2020). Furthermore, repair and rework (IF2) costs contribute significantly to internal failure expenses, with studies showing that 6% to 15% of total construction costs result from defective materials and rework expenses (Yarnold et al., 2021). Quality improvement programs (P8), using methodologies such as Six Sigma, Lean, and PDCA cycles, are particularly effective in preventive cost optimization.

While VF are often prioritized in quality management strategies, HF such as strategic planning (P1) and data analysis (P7) are frequently overlooked, despite their crucial role in cost reduction and process efficiency. Strategic planning enables organizations to align quality initiatives with business objectives, mitigating cost overruns and inefficiencies (Tawfek et al., 2012). Additionally, effective quality data management (P7) allows firms to track and predict quality-related costs, minimizing delays and preventing rework expenses. Without a systematic approach to data-driven decision-making, organizations risk misallocating resources, leading to higher failure costs and inefficient cost structures. This underscores the need for an integrated approach combining VF and HF to enhance COQ performance and ensure long-term cost optimization.

The PLS-SEM model findings further reveal insights into COQ cost interactions. The study found that H1 (Prevention → Internal Failure), H2 (Internal Failure → External Failure), and H4 (Quality Professionals' Role in COQ Optimization) were not statistically significant. While these hypotheses suggested potentially positive relationships, they did not yield statistical validation ($\beta = 0.186$, $p = 0.081$; $\beta = 0.180$, $p = 0.179$; $\beta = 0.107$, $p > 0.05$, respectively). This aligns with previous research, indicating that higher appraisal costs do not always translate into immediate reductions in internal failure costs due to time lags in quality improvement processes. Similarly, the absence of a direct relationship between internal and external failure costs suggests that poor internal failure monitoring may not necessarily lead to external failure cost reductions (Quinn & Bhatty, 1989), the impact of quality professionals in COQ optimization varies across organizations, depending on company policies, project scope, and available resources (Schiffauerova & Thomson, 2006). Conversely, H3 (Prevention → External Failure) was statistically significant. The findings confirm that prevention costs have a strong positive influence on external failure costs ($\beta = 0.465$, $p < 0.05$). This reinforces the argument that investment in preventive quality measures significantly reduces overall failure rates (Kiani et al., 2009). Organizations prioritizing ISO 9001-based quality frameworks demonstrate higher COQ efficiency, as structured quality management systems streamline defect prevention (Glogovac & Filipovic, 2018). Further examination suggests that higher prevention investments lead to lower failure costs, as increased spending on staff training, process improvements, and technological advancements mitigates defects and rework-related expenses. However, organizations must maintain a balance between prevention and appraisal investments to avoid over-allocation of resources (Hall & Tomkins, 2001). Achieving an optimal COQ strategy involves ensuring equilibrium between prevention, appraisal, and failure costs, where quality objectives are met while controlling total expenditure. Overall, the study underscores the critical role of VF, HF, and proactive quality investment in optimizing COQ in construction projects. The findings reinforce the need for strong managerial commitment, data-driven quality management, and strategic investments in preventive measures to achieve long-term cost efficiency and enhanced quality performance.

Table 4: Path coefficients and significance values

Hypothesis	Path coefficient	T statistics (|O/STDEV|)	P values	Statistical support
H1: Prevention -> Internal Failure	0.186	4.610	0.081	Not Supported
H2: Internal Failure -> External Failure	0.180	1.345	0.179	Not Supported
H3: Prevention -> External Failure	0.465	1.828	0.000	Supported
H4: Role -> COQ	0.107	1.591	0.112	Not Supported

6. CONCLUSION

The integration of COQ techniques into the construction industry signifies a pivotal advancement toward more strategic and data-driven quality management. This transition supports a broader shift from reactive defect control to preventive, system-oriented quality assurance frameworks aligned with sustainability, lifecycle performance, and long-term value creation. However, the full potential of COQ remains underleveraged due to limited awareness of HF such as strategic planning, organizational alignment, and quality data utilization elements that profoundly shape quality outcomes but often remain obscured in conventional models. This study systematically identified and validated 22 influencing factors, categorized into VF and HF, and organized them into four thematic dimensions. This structured taxonomy enhances stakeholders' ability to diagnose inefficiencies and design targeted interventions within quality management systems. Notably, VF such as staff training and process standardization serve as immediate levers for reducing defects and rework, while HF such as strategic quality planning and digital data monitoring are shown to drive long-term cost efficiencies and organizational learning. The model, evaluated using PLS-SEM, demonstrated that prevention costs have a statistically significant inverse relationship with external failure costs ($\beta = 0.465$, $p < 0.05$), supporting the strategic value of preventive investments. Conversely, the hypothesized links between internal and external failure costs, and between prevention and internal failure, did not attain statistical significance, suggesting potential moderating variables or context-dependent dynamics that merit further investigation.

From a theoretical perspective, the study contributes to the refinement of COQ theory by incorporating complexity-informed constructs and validating their operational interdependencies. Practically, it offers a diagnostic framework for construction firms to benchmark COQ performance and prioritize quality investments that yield measurable cost benefits. Nonetheless, certain limitations warrant consideration. The study's geographic scope was restricted to Indian construction professionals, and data were collected cross-sectionally, which may limit temporal and contextual generalizability. Moreover, reliance on self-reported perceptions introduces potential biases. Future research should focus on developing a standardized, region-sensitive COQ index to enable cross-context comparisons and enhance model applicability. Furthermore, longitudinal investigations leveraging real-time project data and AI-driven quality analytics are also recommended to capture dynamic quality-cost trade-offs over time. This study offers a foundational yet adaptable model for understanding and operationalizing COQ in construction. By integrating quantitative rigor with industry-specific insights, it paves the way for more efficient, transparent, and sustainable quality management practices across diverse construction environments.

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8. **ANNEXURE:** Model development

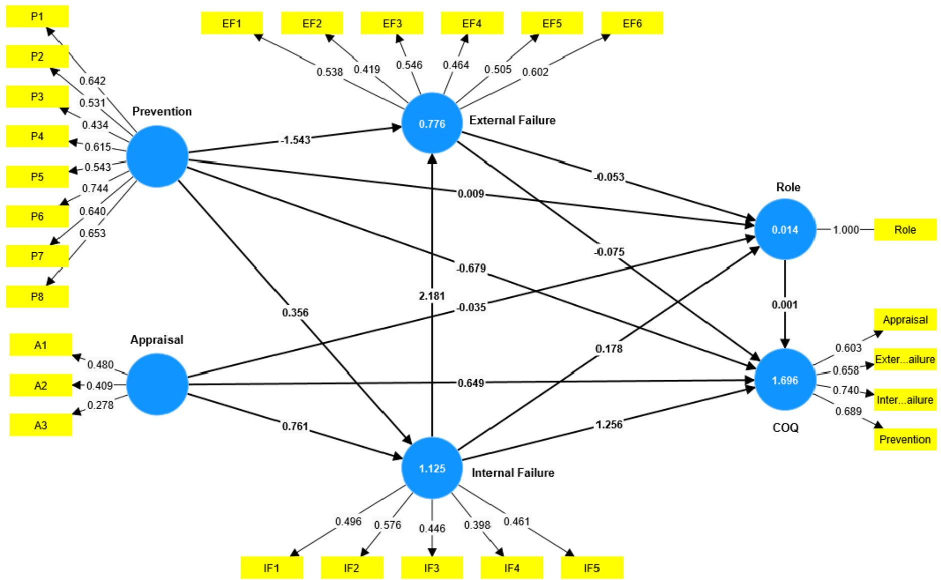

Figure A: Development of model – Phase 1

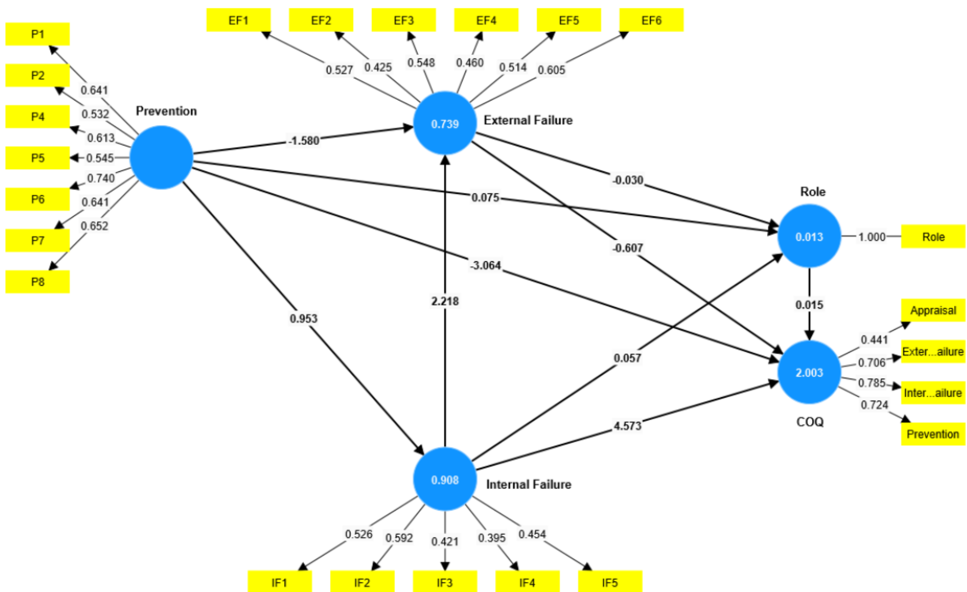

Figure B: Development of model – Phase 2

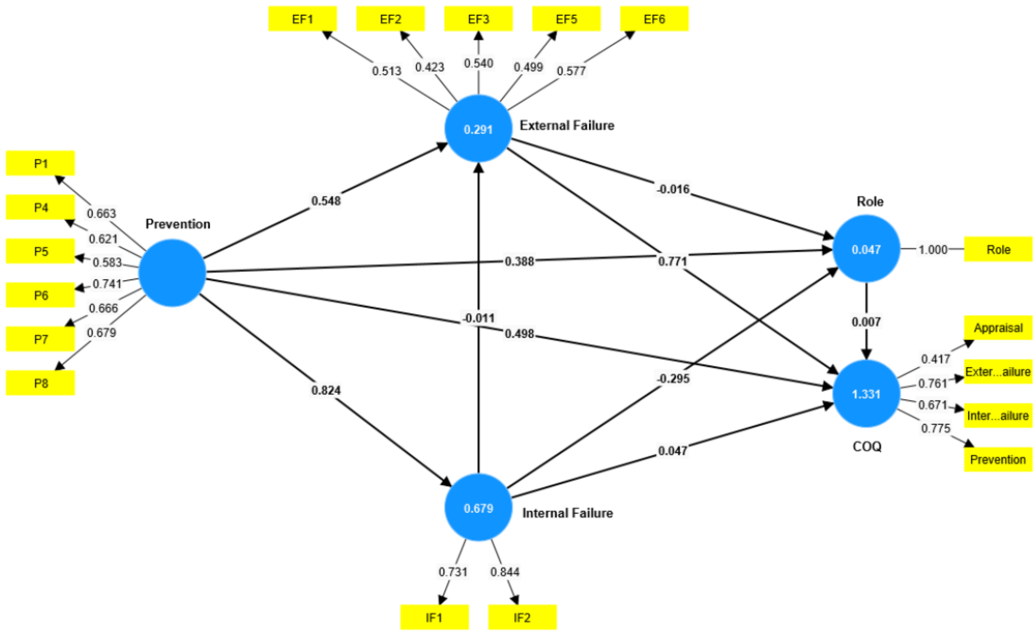

Figure C: Development of model – Phase 3 (Final Version)

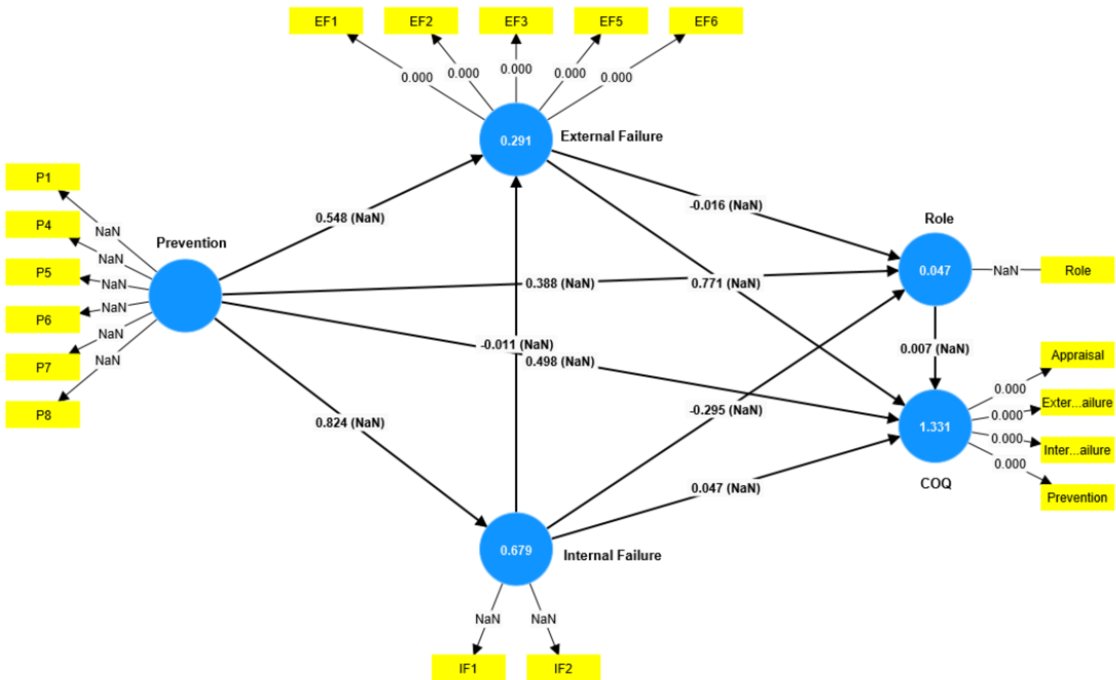

Figure D: Bootstrapping of the final model