Evaluating Factors Influencing Quality Assurance of Building Construction Projects: A PLS-path Modelling Approach

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Abstract

The quality of building construction projects in Kenya has been a challenge throughout recent years. Despite the presence of regulatory agencies, buildings have continued to portray a significant lack of quality with several buildings collapsing in major towns. The purpose of this study was to evaluate factors influencing quality assurance of building projects as well as to determine the magnitude of the influence. Eight indicators of quality assurance were identified from ISO 9001 elements of quality assurance. Similarly, eleven factors influencing quality assurance with five indicators each were identified from literature. A questionnaire survey of building contractors was carried out to evaluate factors influencing quality assurance of building construction projects. The findings of the survey were analysed using SPSS and SmartPLS to determine which studied factors were most critical. Findings indicated the most critical factors as; contractor related factors, consultant related factors, inspection and supervision related factors, communication related factors, and quality standards and measurements related factors. The least ranked factors were equipment related, and health and safety related factors. All eleven factors were however found to have significant influence on quality assurance of building construction projects. The findings of this study are important in highlighting critical areas in which contractors should channel resources to enhance quality assurance of building projects.

Keywords: Contractors; Factors influencing quality assurance; Quality assurance

Introduction

The importance of the construction sector in any economy cannot be overemphasized. In Kenya, the sector accounted for 5.3% of the county's GDP in 2022 (KNBS, 2022) indicating the value and contribution it has to the economy. As such, the successful completion of building projects is paramount. A successful building construction depends not only on achieving the project cost and time constraints but also meeting required quality standards. Quality in construction conveys the concept of compliance with a defined requirement, value for money, fitness for purpose and customer satisfaction (Hu & He, 2014).

Poor quality of building projects has however been a continuous challenge in the construction industry. Poor quality in construction leads not only to time and cost overruns, but also reduced health and safety, environmental damage, and loss of reputation (Fernandez, 2014). Lack of adherence to quality standards may lead to failure of the structure and ultimate collapse leading to loss of lives and property (Awoyera et al., 2021). Poor quality can adversely influence the reputation of the client, consultants and contractor. It can have adverse effects on the opportunities for repeat business. Maheshkumar and Purva, (2016) noted that poor quality can significantly influence the programme if rework is required since resources are diverted from other activities to rectify quality defects. The same authors also noted that poor quality affects the environment through the need to replace materials hence additional raw materials, transportation of required materials thus increased carbon emissions and disposal of waste materials from rework that may be dumped in landfills. Improved quality is therefore a necessary

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change in the construction industry and it is necessary to identify factors influencing quality assurance and the magnitude of their influence in an attempt to minimize and eventually eradicate the influencing factors thus enhancing quality.

Quality in Building Construction

Quality in construction is considered in terms of quality assurance, quality control, and quality management (Asim et al., 2014). Quality assurance and quality control are quality processes that are intertwined together in the broader quality management. Quality assurance in construction involves those practices that are implemented in the project to ensure that the standard of the work is consistent in terms of quality (Caldas et al., 2015).

According to Tim Howarth and Paul Watson, (2011), quality assurance is concerned with planning and developing the technical and managerial competence to achieve the desired objectives. These authors added that quality assurance is concerned with the management of people, addressing the roles, duties and responsibilities of individuals in the construction organisation. Irani et al., (2004) highlighted that quality assurance is primarily the responsibility of management, but its structure and implementation are part of the holistic construction organisational framework. Quality assurance is carried out through executing quality activities that help the project team to keep checking the deliverables in the light of predefined requirements.

Poor quality of building construction projects is caused by various factors. Sub-standard building material, inefficient project management, inaccurate building drawings, designs, and specification, poor communication among project team, lack of motivation, inadequate inspection and supervision, ineffective quality management practices, lack of adherence to health and safety practices, poor identification of non-conforming materials, services and products, and lack of engineering geological investigations are causes of poor quality in construction (Burby et al., 2000; Hamma-Adama and Kouider, 2018; Jingmond and Ågren, 2015; Sun and Li, 2013; Wen-jing et al., 2012).

Table 1 presents fifty-five factors affecting quality assurance as obtained from literature review.

Table 1. Factors affecting quality assurance of building projects based on conducted literature review

Factors and Indicators	**Reference**
Management related factors	
Lack of management commitment to continuous quality improvement	Sitota et al., (2021)
Poor application of construction management techniques	Jha & Iyer, (2007)
Inadequate professional capability of respective managers	Sitota et al., (2021)
Lack of quality management systems	Jraisat et al., (2016)
Lack of proper document control	Sheikh et al., (2019)
Designs and specifications related factors	
Lack of design conformance to codes and standards	Sitota et al., (2021)
Errors in design specifications	Sheikh et al., (2019)
Excessive design changes during execution	Hussain et al., (2018)
Faulty project conceptualization	Jha & Iyer, (2007)
Lack of consistency between drawings and specifications	Sitota et al., (2021)
Consultant related factors	
Incompetence of some consultants	Muya et al., (2013)
Receiving kickbacks by some consultants	Muya et al., (2013)
Inefficient team work among consultants	Muya et al., (2013)
Lack of consultant full-time involvement in project	Oyedele et al., (2015)
Poor monitoring and feedback by consultants	Tengan & Danso, 2014)
Contractor related factors	
Contractors' poor technical knowledge and professional expertise	Oyedele et al., (2015)
Making decisions based on cost and not quality of work	Sitota et al., (2021)
Poor coordination of subcontracted work	Sheikh et al., (2019)
Misinterpretation of drawings and specifications	Oke & Dlamini, (2017)

Lack of regular monitoring of site activities	Tengan & Danso, (2014)
Communication related factors	
Poor communication between project team	Tengan & Danso, (2014)
Use of poor channels of communication	Tengan & Danso, (2014)
Inadequate consultation by contractor	Tengan & Danso, (2014)
Lack of teamwork between project participants	Oyedele et al., (2015)
Poor relationships among project participants	Oyedele et al., (2015)
Construction labour related factors	
Use of unskilled trade subcontractors	Oke and Dlamini, (2017)
Poor labour remuneration	Oyedele et al., (2015)
Lack of technical and professional expertise to perform task	Tengan & Danso, (2014)
Inaccurate interpretation of work instructions	Sitota et al., (2021)
Lack of employee training on quality standards	Chan et al., (2006)
Materials related factors	
Poor quality of raw materials	Hussain et al., (2018)
Escalation of material prices	Sitota et al., (2021)
Frequent change in material specifications during construction	Sheikh et al., (2019)
Poor material control, handling and storage	Sitota et al., (2021)
Inadequate material testing and inspection	Sitota et al., (2021)
Equipment related factors	
Poor maintenance of equipment	Sitota et al., (2021)
Use of outdated or low-grade technology in construction processes	Sheikh et al., (2019)
Lack of adequate experience of equipment operator	Sitota et al., (2021)
High cost of appropriate technology and equipment	Sitota et al., (2021)
Lack of calibration of inspection, measuring and testing equipment	Sitota et al., (2021)
Inspection and supervision related factors	
Inadequate supervision by consultants/contractor	Oyedele et al., (2015)
Inadequate inspections by regulatory agencies	Muya et al., (2013)
Lack of on-site project manager	Tengan AND Danso, (2014)
Inadequate skill and experience of supervision team	Sitota et al., (2021)
Lack of commitment by the supervising team	Oke & Dlamini, (2017)
Quality standards and measurements related factors	
Lack of proper quality monitoring and evaluation programs	Hussain et al., (2018)
Lack of documented inspection and test plans	Muya et al., (2013)
Lack of prompt corrective action on poor-quality works	Hussain et al., (2018)
Lack of determination of the cause of nonconformity to avoid recurrence	Oyedele et al., (2015)
Lack of quality audits to ensure that what is intended is actually done in the way as prescribed	Oyedele et al., (2015)
Health and Safety related factors	
Absence of health and safety personnel on site	Mashwama et al., (2017)
Absence of safety manual and related instructions	Chan et al., (2006)
Lack of emphasis on safety and environmental control issues	Chan et al., (2006)
Poor monitoring and supervision of on-site health and safety practices	Mashwama et al., (2017)
Lack of training on site health and safety practices	Chan et al., (2006)

Methodology

The study adopted a survey research design. Sampling was carried out from a list of 3,796 contractors obtained from the 2021 National Construction Authority register in Kenya. A sample size of 341 was calculated using the formula below advanced by Taherdoost, (2018).

$$n = \frac{p\,(100 - p)z^2}{E^2}$$

Where:

n - the required sample size

p - the percentage occurrence of a state or condition

E - the percentage maximum error required

z - the value corresponding to level of confidence required

The formula above was used by Gill et al., (2010) to develop a sample size table (Table 2) based on desired accuracy of 5%, 3% and 1% with confidence level of 95%. From this table the researcher selected a sample size of 341 for an accuracy of 5% and a population size of 3796.

Table 2: Sample size based on desired accuracy with confidence level of 95% (Gill et al., 2010)

	Variance of the population P=50%		
	Confidence level=95% Margin of error		
Population size	**5%**	**3%**	**1%**
50	44	48	50
75	63	70	74
100	79	91	99
150	108	132	148
200	132	168	196
250	151	203	244
300	168	234	291
400	196	291	384
500	217	340	475
600	234	384	565
700	248	423	652
800	260	457	738
1000	278	516	906
1500	306	624	1297
2000	322	696	1655
3000	**341**	787	2286
5000	357	879	3288
10000	370	964	4899

The contractors were sampled using stratified random sampling to cater for the different categories of registration. The size of each stratum based on the category of registration was calculated using the proportionate stratification formula below:

$$n_h = (\frac{N_h}{N})n$$

Where:

n_h- Sample Size (stratum h)

N_h- Population Size (stratum h)

N- Total Population Size

n- Total Sample Size

Eleven factors affecting quality assurance with five indicators each were identified from literature review. A questionnaire was prepared and respondents requested to rate the influence the factors had on the quality assurance of building projects. Likert scale of influence was used (1 - very high influence, 2- high influence, 3- neutral, 4 – high influence, 5- very high influence). Quality Assurance of building projects (QB) was measured using eight indicators obtained from ISO 9001 elements of quality assurance. These where Management responsibility (QB1), Quality management system (QB2), Purchasing (QB3), Process control (PR4), Inspection and testing (QB5), Control of non-conforming work (QB6), Corrective and preventive actions (QB7), and Training (QB8). Respondents were requested to rate the importance of the elements to quality assurance of building projects. Descriptive statistics were analysed using IBM SPSS Statistics version 24 whereas inferential statistics were analysed using smart-PLS version 4.0.9.5 to determine the most critical factors affecting quality assurance and the magnitude of their respective influence.

Findings and Discussion

Respondents' Response Rates

The research elicited a response rate of 57% with 193 questionnaires out of 341 being returned. A response rate of 50% and above is considered adequate (Mugenda and Mugenda, 2003).

Factors affecting quality assurance

Eleven factors affecting quality assurance were assessed to determine which factors significantly influenced quality assurance of building projects in Kenya. Eight factors were rated as having very high influence since they had a mean of between 4.21 - 5.00. Quality standards and measurements factors, equipment factors, and Health and Safety related factors were rated as having high influence since they had a mean of between 3.41 - 4.20. Generally, all eleven factors significantly influenced quality assurance of building projects and were included in the model.

Structural equation modelling using component based Partial Least Squares

The study employed structural equation modelling, specifically component-based partial least squares (PLS-SEM) to ascertain the correlations between quality assurance and its determinants. Regression models, path analyses, confirmatory factor analyses, second-order factor analyses, covariance structure models, and correlation structure models were all done with PLS-SEM (Henseler et al., 2009). It enables the investigation of the linear correlations between the manifest variables and latent constructs. Essentially, SEM allows several relationships to be examined simultaneously in a single model with multiple relationships rather than looking at each relationship separately.

After a thorough analysis of the literature on quality management, structural equation model was created using component-based PLS path modelling. The model is presented as:

$$y_{ik} = \alpha_k + \sum_{i=1}^{n} (\beta_{jk} x_{ij}) + \varepsilon_{ik}$$

Where:

- y_{ik} is the k^{th} criterion variable (quality assurance of building projects) for the i^{th} observation;
- α_k is the regression intercept for the k^{th} criterion variable;
- β_{jk} is the j^{th} predictor variable's (x_j) regression slope for the k^{th} criterion variable (y_k);
- x_{ij} is the j^{th} predictor variable (factors influencing quality assurance of building projects) for the i^{th} observation;
- ε_{ik} is the error of fit for the k^{th} criterion variable in the i^{th} observation.

Eleven hypotheses were established, with 55 attributes assigned to the eleven enablers and eight attributes assigned to the outcomes as indicated in Table 3.

Using smart-PLS version 4.0.9.5, the simulation work was done to determine how the observed variables and their latent constructs affected quality assurance. In social science studies, PLS-SEM is currently recognized and chosen as the technique that is most suitable for a multivariate analysis (Hair et al., 2011). According to Ringle et al., (2021), there are two components to a PLS path model. First, a structural model that connects the constructs (presented as ovals or circles). In the context of PLS-SEM, this model is referred to as the inner model. The connections (paths) between the constructs are also shown by the structural model. Second, there are the measurement models of the constructs, which show the connections between the constructs and the indicator variables (presented as rectangles) and are also called the outer models in PLS-SEM.

Evaluation of outer measurement model

The objective of the external measurement model is to determine the validity, internal consistency, and reliability of both the unobserved and observed variables (Ho, 2013). Convergent and discriminant validity were used to assess validity, while single observed and construct reliability tests were the basis for consistency evaluations (Hair et al., 2013).

By assessing the standardized outer loadings of the observed variables, a single observed variable reliability characterizes the variance of an individual observed in relation to an unobserved variable (Götz et al., 2010). It is considered that observed variables with an outer loading of 0.7 or higher are highly acceptable (Hair et al., 2013), whereas the outer loading ought to be discarded if its value is less than 0.7 (Hair et al., 2011). For this study, the approved cut-off value for the outer loading was 0.7. The internal consistency assessment in the construct reliability was conducted using Cronbach's alpha and composite reliability. Nevertheless, because composite reliability preserves the standardized loadings of the observed variables, it was thought to be a superior measure of internal consistency than Cronbach's alpha (Hussain et al., 2018). Table 3 demonstrates that all constructs had Cronbach's alpha and composite reliability values greater than 0.80, despite the fact that the composite reliability and Cronbach's alpha analyses were similar. All of the latent construct values exceeded the minimal threshold level of 0.70, as demonstrated by the Cronbach's alpha and composite reliability, which also suggested that the scales were reasonably reliable.

The Average Variance Extracted (AVE) for each latent construct was determined in order to confirm the variables' convergent validity (Hussain et al., 2018). The latent constructs in the model ought to account for the lowest 50% of the variance from the observed variable. Hair et al., (2011) suggested that all constructs' AVEs should be greater than 0.5. Table 3 shows that every AVE value was greater than 0.5, indicating that the study model's convergent validity was verified. These results confirmed the convergent validity and good internal consistency of the measurement model.

Table 3. Results of construct reliability and validity

No.	Factors	Path Coefficients	Cronbach's Alpha	AVE
1.	Management related factors	-0.267	0.859	0.654
2.	Designs and specifications related factors	-0.255	0.846	0.597
3.	Consultant related factors	-0.286	0.859	0.619
4.	Contractor related factors	-0.270	0.899	0.607
5.	Communication related factors	-0.254	0.873	0.662
6.	Construction labour related factors	-0.243	0.869	0.621
7.	Materials related factors	-0.240	0.854	0.641
8	Equipment related factors	-0.243	0.858	0.663
9.	Inspection and supervision related factors	-0.230	0.845	0.618
10.	Quality standards and measurements related factors	-0.247	0.873	0.634
11.	Health and Safety related factors	-0.236	0.889	0.687

The discriminant validity of the latent constructs was the next endeavour. When the latent variable's cross-loading value is higher than that of any other construct in the path model, the manifest variable in that construct is said to be discriminately valid (Sarstedt et al., 2014). The discriminant validity was assessed using cross-loadings and the Fornell and Larcker criterion (Hussain et al., 2018). According to Sarstedt et al., (2014), a construct should not exhibit the same variance as any other construct that is greater than its AVE value. The Fornell and Larcker criterion test of the model, which compares the squared correlations with the correlations from other latent constructs, is presented in Table 3. According to this table, all of the correlations were less than the diagonally applied squared root of average variance, suggesting adequate discriminant validity. This demonstrated that each construct's observed variables corresponded to the specified latent variable, supporting the discriminant validity of the model. Table 3 also highlights that for every observed variable in the model, the cross-loading was greater than the inter-correlations of the construct for every other observed variable. Consequently, these results supported the cross-loadings assessment criteria and offered sufficient support for the measurement model's discriminant validity. With the verification of the research model, convergent validity, discriminant validity, and confirmation of adequate reliability, the proposed conceptual model was therefore expected to be acceptable.

Table 4. Results of Fornell–Larcker criterion test

Factor	CL	CN	CO	CS	DS	EQ	HS	IN	MF	MT	QF
Construction labour related factor (CL)	**0.894**										
Contractor related factor (CN)	0.796	**0.798**									
Communication related factor (CO)	0.703	0.689	**0.701**								
Consultant related factor (CS)	0.558	0.581	0.62	**0.734**							
Design and specifications related factors (DS)	0.347	0.300	0.273	0.193	**0.865**						
Equipment related factor (EQ)	0.534	0.272	0.356	0.292	0.478	**0.741**					
Health and safety related factor (HS)	0.799	0.800	0.576	0.703	0.384	0.296	**0.719**				
Inspection and supervision related factor (IN)	0.725	0.499	0.438	0.523	0.549	0.604	0.491	**0.833**			

Management control related factor (MF)	0.882	0.601	0.608	0.648	0.586	0.306	0.514	0.609	**0.791**		
Materials related factor (MT)	0.591	0.346	0.363	0.425	0.224	0.31	0.344	0.431	0.456	**0.726**	
Quality standards and measurements related factors (QF)	0.463	0.568	0.577	0.812	0.867	0.251	0.33	0.742	0.608	0.866	**0.794**

Evaluation of inner measurement model

Measuring the inner structural model outcomes comes next, after the model's validity and reliability have been established. This involved looking at the relationships between the constructs and the predictive relevancy of the model. The most important metrics for assessing the inner structural model are the coefficient of determination (R^2), path coefficient (β value), T-statistic value, effect size (f^2), predictive relevance of the model (Q^2), and Goodness-of-Fit (GOF) index.

Measuring the R^2 Value

The structural model's overall effect size and variance explained in the endogenous construct are measured by the coefficient of determination, which also serves as a predictability indicator for the model. The study's quality endogenous latent construct had an inner path model of 0.675. This suggests that eleven independent constructs accounted for 67.5% of the variance in quality assurance, implying that eleven latent constructs in the model accounted for approximately 67.5% of the change in quality assurance. According to Henseler et al., (2009), and Hair et al., (2013), an R^2 of 50 is viewed as moderate, an R^2 value of 0.25 is regarded as weak, and an R^2 value

of 0.75 as substantial. For this reason, the study's R^2 value was moderate.

Estimation of Path Coefficients (β) and T-statistics

The standardized β coefficient in the regression analysis and the path coefficients in the PLS were comparable. The significance of hypothesis was examined using the β value. For every unit variation in the independent construct(s), the dependent construct's expected variation was indicated by the symbol β. Every path in the proposed model had its β value calculated; the higher the β value, the more significant the effect on the endogenous latent construct. The T-statistics test was required to confirm the significance level of the β value. According to Cohen, (2013) the significance of hypothesis can be assessed using the bootstrapping technique. For this study, a bootstrapping procedure using 5000 subsamples with no sign changes was used to test the significance of the path coefficient and T-statistics values (Table 5).

Table 5. Results of Path coefficient and T-statistics

	Hypothesized Path	**Standardized Beta**	**T-test**	***p* values**
H_1	Management related factors -> Quality Assurance	-0.247	10.979	0.000
H_2	Designs and specifications related factors-> Quality Assurance	-0.255	10.036	0.000
H_3	Consultant related factors-> Quality Assurance	-0.236	10.612	0.000
H_4	Contractor related factors-> Quality Assurance	-0.230	10.513	0.000
H_5	Communication related factors-> Quality Assurance	-0.243	10.604	0.000
H_6	Construction labour related factors-> Quality Assurance	-0.254	10.971	0.000
H_7	Materials related factors-> Quality Assurance	-0.267	10.996	0.000
H_8	Equipment related factors-> Quality Assurance	-0.270	10.602	0.000

H_9	Inspection and supervision related factors-> Quality Assurance	-0.240	10.883	0.000
H_{10}	Quality standards and measurements related factors-> Quality Assurance	-0.243	10.522	0.000
H_{11}	Health and Safety related factors -> Quality Assurance	-0.286	10.518	0.000

A negative coefficient of β indicates that the dependent variable tends to decrease as the independent variable rises. In H_1, it was predicted that the lack of adherence to management related factors has a negative influence on quality assurance practices of building projects. As predicted, the findings in Table 6 and Figure 1 confirmed that lack of adherence to management related factors, negatively affects quality assurance practices of building projects (β = -0.247, T = 10.979, p = 0.000). H_1 therefore had substantial backing. Regarding the direct and adverse impact of noncompliance with designs and specifications (H_2), Table 6 and Figure 1 results verified that noncompliance with designs and specifications related factors adversely affected building project quality assurance procedures (β = -0.255, T = 10.036, p = 0.000).

H_3 was supported because of the negative and significant impact that noncompliance with consultant-related factors had on quality assurance procedures (β = -0.236, T = 10.612, p = 0.000). H_4 on the other hand was supported by the significant effect of noncompliance with contractor-related factors on building project quality assurance (β = -0.230, T = 10.513, p = 0.000). Similarly, H_5 was empirically supported by Table 5 and Figure 1 findings, which showed that noncompliance with communication-related factors had a negative and significant influence (β = -0.243, T = 10.604, p = 0.000), supporting the hypothesis.

H_6 projected that the practices of quality assurance in building projects are negatively impacted by noncompliance with construction labour related factors. As expected, Table 6 and Figure 1 results verified that noncompliance with construction labour related factors influencing quality assurance has a negative impact on building projects' quality assurance practices (β = -0.254, T = 10.971, p = 0.000). H_6 therefore received significant support. The results of Table 6 and Figure 1 supported the hypothesis that the practices of quality assurance in building projects were adversely affected by noncompliance with materials-related factors, when considering the direct and negative impact of this noncompliance on quality assurance (H_7) (β = -0.276, T = 10.996, p = 0.000).

H_7 was supported because of the negative and significant impact that noncompliance with equipment-related factors had on building projects' quality assurance practices (β = -0.270, T = 10.602, p = 0.000). Similarly, H_8 was supported by the significant impact of noncompliance with equipment-related factors (β = -0.270, T = 10.602, p = 0.000). H_9 was supported by the significant impact of noncompliance with inspection and supervision related factors on building project quality assurance practices (β = -0.240, T = 10.883, p = 0.000). In similar manner, Table 6 and Figure 1 presented results which offered empirical support for H_{10}, demonstrating that the hypothesis was confirmed by the negative and significant influence of factors related to measurements and noncompliance with quality standards (β = -0.243, T = 10.522, p = 0.000). Finally, the hypothesis was confirmed by the negative and significant influence of health and safety-related factors on quality assurance practices of building projects (β = -0.286, T = 10.518, p = 0.000).

The stronger the impact of an exogenous latent construct on the endogenous latent construct, the higher the beta coefficient (β). Comparing the contractor related factor to other β values in the model, Table 5 and Figure 1 revealed that it had the highest path coefficient of β = -0.230, indicating a higher variance and significant impact on the quality assurance of building projects. Conversely, with β = -0.286, the factor related to health and safety had the least significant impact on building projects' quality assurance. Table 6 presents the path coefficient and t-statistics for the eleven hypotheses in order of significance

Table 6. Results of path coefficient and T-statistics in order of significance

Hypothesized Path	Standardized Beta	T-test	p values
Contractor related factors-> Quality Assurance	-0.230	10.513	0.000
Consultant related factors-> Quality Assurance	-0.236	10.612	0.000
Inspection and supervision related factors-> Quality Assurance	-0.240	10.883	0.000
Communication related factors-> Quality Assurance	-0.243	10.604	0.000
Quality standards and measurements related factors-> Quality Assurance	-0.243	10.522	0.000
Management related factors -> Quality Assurance	-0.247	10.979	0.000
Construction labour related factors-> Quality Assurance	-0.254	10.971	0.000
Designs and specifications related factors-> Quality Assurance	-0.255	10.036	0.000
Materials related factors-> Quality Assurance	-0.267	10.996	0.000
Equipment related factors-> Quality Assurance	-0.270	10.602	0.000
Health and Safety related factors -> Quality Assurance	-0.286	10.518	0.000

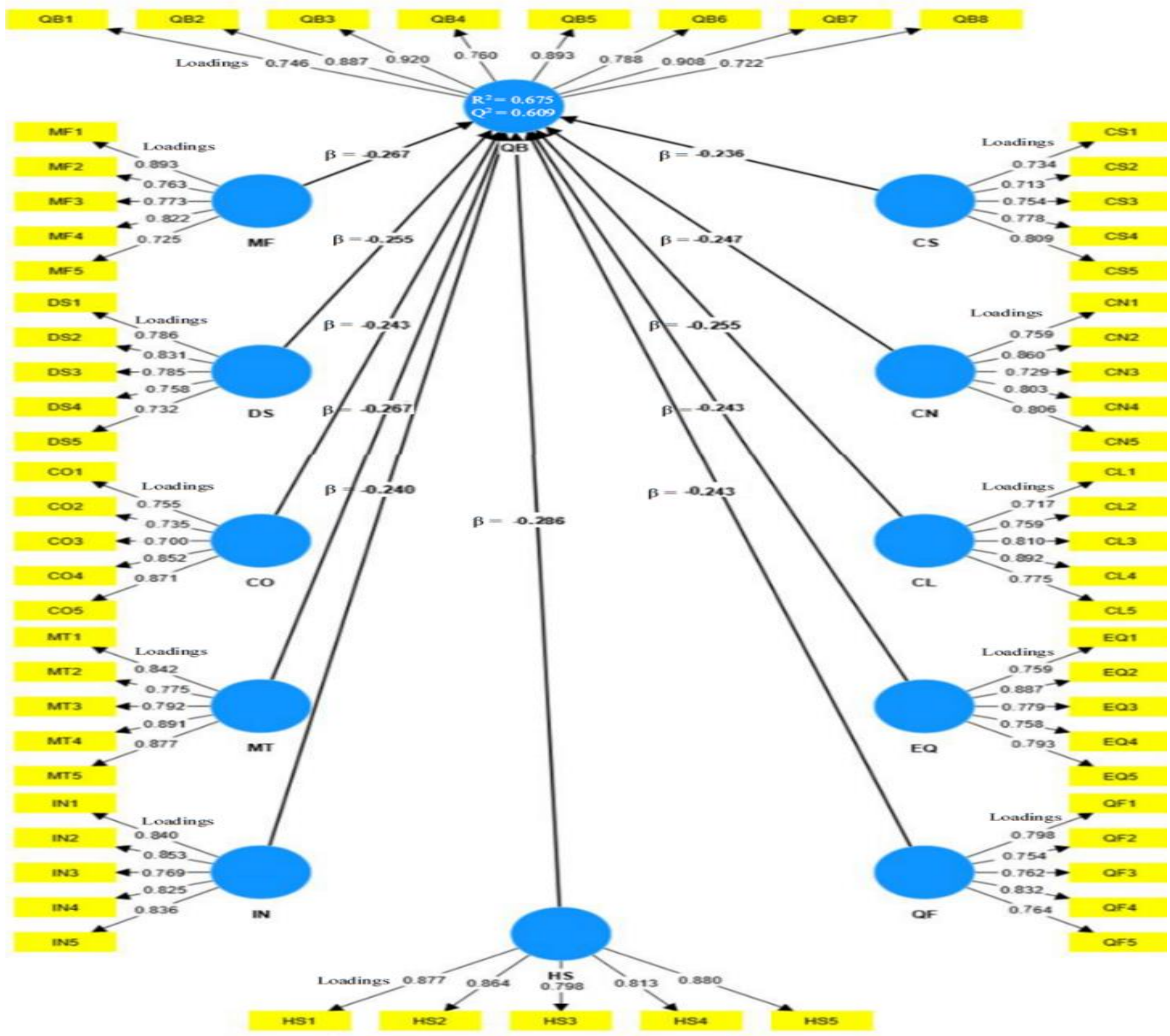

Figure 1. PLS -SEM path model for quality assurance of building projects

Measuring the Effect Size (f2)

The degree to which each exogenous latent construct influences the endogenous latent construct is indicated by the f^2 value. The removal of an independent construct from the path model modifies the coefficient of determination (R^2) and establishes whether the value of the latent endogenous construct is significantly impacted by the removed latent exogenous construct. According to Cohen, (2013), f^2 values greater than or equal to 0.35 are considered to have a strong effect, values greater than or equal to 0.15 are considered to have a moderate effect, whereas values greater than or equal to and 0.02 are considered to have a weak effect. The f^2 from the SEM computations is displayed in Table 7. According to Cohen, (2013), the value of R^2 was moderately impacted by the f^2 of each of the eleven exogenous latent constructs on quality assurance of building projects. Additionally, the study's eleven independent latent constructs all contributed to the dependent variable's R^2 value of 67.5%.

Table 7: Results of effect size

Exogenous Latent Variables	Effect Size f^2	Total Effect
Management related factors	0.227	Moderate
Designs and specifications related factors	0.218	Moderate
Consultant related factors	0.294	Moderate
Contractor related factors	0.301	Moderate
Communication related factors	0.231	Moderate
Construction labour related factors	0.218	Moderate
Materials related factors	0.212	Moderate
Equipment related factors	0.211	Moderate
Inspection and supervision related factors	0.240	Moderate
Quality standards and measurements related factors	0.230	Moderate
Health and Safety related factors	0.124	Moderate

Predictive Relevance of the Model (Q2)

According to Tenenhaus et al., (2005), the PLS path model's quality is determined by Q^2 statistics, which are computed using blindfolding techniques and cross-validated redundancy. The Q^2 criterion recommends that the conceptual model can predict the endogenous latent constructs (Hussain et al., 2018b). The current PLS software packages typically estimate Q^2 with an omission distance of 5–10. By convention, a cross-validated redundancy $Q^2 > 0.5$ is considered to be a predictive model (Akter et al., 2011). The study's Q^2 of 0.609, shown in Figure 1, was obtained with an omission distance of 7, indicating a highly predictive model. Thus, the study model's Q^2 values corroborate the notion that the path model's predictive relevance for the endogenous construct was sufficient.

Goodness-of-Fit Index (GoF)

Tenenhaus et al., (2005) stated that the complete model fit is evaluated using the Goodness-of-Fit (GoF) index to ensure that the model adequately explains the empirical data. The range of the GoF index is 0 to 1. Vinzi et al., (2010) noted that the GoF index is descriptive in nature, and therefore there are no inference-based standards to determine its statistical significance. But according to Wetzels et al., (2009), in order to establish GoF_{small} (0.10), GoF_{medium} (0.25), and GoF_{large} (0.36) as baselines for validating the PLS-based models, one should use 0.50 as the cutoff value for communality and various effect sizes of R^2.

A parsimonious and credible model is demonstrated by a good model fit (Henseler et al., 2009b). According to Hussain et al., (2018), the average R^2 value and the geometric mean value of the average communality (AVE values) are used to calculate the GoF. The GoF index for this study model was determined from Table 8 to be 0.641, indicating that empirical data fits the model satisfactorily and has a significant predictive power when compared to baseline values.

Table 8. Results of Goodness-of-Fit index calculation

Construct	AVE	R^2
Management related factors	0.654	
Designs and specifications related factors	0.597	
Consultant related factors	0.619	
Contractor related factors	0.607	
Communication related factors	0.662	
Construction labour related factors	0.621	
Materials related factors	0.641	
Equipment related factors	0.663	
Inspection and supervision related factors	0.618	
Quality standards and measurements related factors	0.634	
Health and Safety related factors	0.687	
Quality Assurance of Building Projects	0.644	0.675
Average Values	7.647	0.675
$AVE \times R^2$	0.411	
$GoF = \sqrt{(AVE \times R^2)}$	0.641	

The Standardized Root Mean Square Residual

According to Chen (2007), the Standard Root Mean Square Residual (SRMSR) is an index that represents the mean of the standardized residuals between the predicted and observed covariance matrices. An indicator of estimated model fit is the SRMSR. According to Hussain et al., (2018), the study model fits well when SRMSR = <0.08, with a lower SRMSR indicating a better fit. The study model's SRMSR was 0.051, Chi-Square was equal to 1013.152, and NFI was equal to 0.739, as shown in Table 9, indicating a good fit.

Table 9. Results of model fit summary

	Estimated Model
SRMR	0.051
d_ULS	1.641
d_G1	0.872
d_G2	0.785
Chi-Square	1013.152
NFI	0.739

Conclusion

The importance of quality assurance in construction cannot be over emphasized and any initiative towards improvement of quality is received positively. The benefits of improved quality assurance to a construction company include increased cost saving, minimized risk of time and cost overruns, reduced cases of litigation, improved customer satisfaction, improved project management, improved productivity, increased efficiency, and enhanced safety.

Evaluation of factors influencing quality assurance of building construction projects identified contractor related factors, consultant related factors, and inspection and supervision related factors as the most critical. These factors were closely followed by communication related factors, quality standards and measurements related factors, management related factors, construction labour related factors, designs and specifications related factors, materials related factors, equipment related factors, and health and safety related factors. The above eleven factors accounted for approximately 67.5% of the change in quality assurance thereby indicating significant influence. In addition, the R^2 value indicated that the model predicted 67.5% of the relationship.

Recommendations

Identification of factors affecting quality assurance and the influence each factor has on quality is important to any construction company. It helps guide the contractor on critical areas to focus on to ensure the project complies with the defined requirements, offers value for money, provides fitness for purpose, and achieves customer satisfaction.

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