

Effectuated Factors on Standard Measurement Method Adoption in Construction Projects Using SEM Approach

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ABSTRACT

Various factors affect the standard method of measurement adoption in civil construction projects, especially in developing countries such as Malaysia. Hence, this study investigates the relationship between affected factors towards standard adoption using the SEM approach. As a case study, this study focused on quantity surveyors working at a consulting firm in Selangor, Malaysia. This study identifies the effect of standard measuring technique adoption in Malaysian building projects that have a beneficial impact. The factors research model is the first stage in determining the reasons for using the most recent standard measuring technique in civil engineering construction projects and explaining the link between the barrier factors and standard adoption. The information was gathered using a questionnaire survey sent to participants at construction firms that used the standard measurement method. The PLS-SEM approach was used by SmartPLS 3 software to construct and assess a hierarchical model to assess variables and their effects on measuring method adoption. The findings revealed that 17 barrier factor indicators had a significant impact on adopting the standard assessment technique. The coefficient of determination (R^2 value) of 0.307 represents the proportion of variance in the dependent variable that one or more predictor variables can explain. Furthermore, the conceptual model's predictive significance value Q^2 is 0.156 greater than zero, indicating that it can predict endogenous latent components. The measured effect size (f^2) between the barrier factors (exogenous latent) and the adoption of the model's standard (endogenous latent) was 0.443, indicating that the developed model had significant explanatory power to represent the relationship among the variables of the factors and the effect on measurement method adoption. There is a need to improve the methods and increase the driver elements described in this study to promote the adoption of standard measurement in construction projects, which impacts the adoption of the standard method of measuring. In the future, researchers can start from this study to compare the situation in Malaysia with developed countries to discover shortcomings and develop a framework for measurement factors that can be applied.

Keywords: Standard measurement method; effectuated factors; construction projects; structural equation modelling

INTRODUCTION

According to Cartlidge (2011), every cent invested in the building sector would result in a penny loss due to standard and uniform limitations. As a result, the construction industry must follow strict building documentation and information requirements to ensure the sector's productivity within the national economy (Nizam Akbar et al. 2015). A collection of measured works or items and guidelines to lead the tendering contractor in permitting against the measured things may make up the standard measuring method (Molloy 2007). According to the Chartered Surveyors (2003), the standard serves as a manual that contains the required measurements for building and civil engineering projects. The standard

ensures that the amount and quality of the work are correctly represented in the created bill of quantity. It is possible to use this standard to accomplish cost-effective projects that follow the same criteria in similar work because there is less uncertainty toward the contractor (Uthpala and Indunil 2013). Standardization aims to reduce waste, overpayment, mismanagement, and disputes (Hansen and Salim 2015).

A quantity surveyor's job entails making extensive lists that enable the standard to be applied. A quantity surveyor's regular service is to have a quantity list (Adnan et al. 2011). In addition, quantity surveyors often provide feasibility studies, costs, and planning schedules (Ahmed et al. 2018). The bill of quantities is often associated with using the standard measurement method. The bill

of quantities is a standardized document that helps the contractor make reliable calculations or operate on several projects simultaneously, resulting in a fair and transparent bid (Hansen and Salim 2015). However, the regulations of this standard measuring system encourage the inaccuracy of quantities in the quantity list by inaccuracies in rates and quantities in highly sophisticated standard measurement techniques, such as in Australia. According to Davis and Baccarini (2004), when compared to routine measurement procedures, there are specific problems with amounts in construction as described by (Bandi and Abdullah, 20). If these quantities are incorrect, a problem will arise, and contractors will be unhappy with how the quantity is used in the bill of quantity (Adnan et al. 2011).

AFFECTED FACTORS TO MEASUREMENT STANDARD ADOPTION

Even though the importance of standard measurement methods in preparing a bill of quantities has recently increased, their use and implementation continue to face challenges. Any contractor who joins the project tender will have the exact information and a common understanding of the work if the standard document is utilised, where all scope of work is clearly and often defined. The provision also decreases or eliminates the expense of tendering uncertainty, allowing for a more objective and straightforward range of eligible contractors. Indirectly, it simplifies contract management and eliminates project expense ambiguity. Despite the abundance of studies on the standard measurement adaptation method, attempts to evaluate related studies are still lacking systematically. The article addresses and characterizes the standard method of measurement acceptance in the construction industry to close the gap incomprehension. However, as consultants, contractors, and clients in construction projects know, this standard measurement method has not been widely adopted.

Measuring construction work is essential for the budget. A quantity surveyor working on building and civil engineering projects would typically work from a bill of quantities based on architectural and engineering drawings (Hansen & Salim 2015; Nizam Akbar et al. 2015, 2018). The bill of quantities should be prepared systematically to prevent disputes. In this way, the uniformity measurement approach should also be standardized. For building projects, the Malaysian Standard Method of Measurement of Building Works (SMM2) was used, while for civil engineering projects,

the Malaysian Civil Engineering Standard Measurement Method (MyCESMM) was utilised (Ganiyu & Mohamed 2012; Hassan 2011; Nizam Akbar et al. 2018).

One of the problems that prompted the study was using a different standard measurement method, resulting in unevenness. Consultants used traditional in-house measurement methods, such as classification and description of the same object in different ways, according to Molloy (2007). Meanwhile, Ganiyu & Mohamed (2012) reported that a survey conducted by RICS revealed that 46 standard measurement methods exist in each of the world's 27 countries. Nonetheless, according to a literacy report, some countries use a range of traditional measurement methods but are not included in the study. This problem has also been proven by (Nizam Akbar et al. 2018), which revealed no data from the worldwide survey database (RICS 2003). Malaysian RICS members did not research the present standard measuring system utilised in Malaysia. Even though the research period (2003 to 2018) had a significant gap, Malaysia's key construction industry participants nevertheless referenced various measuring techniques for construction and civil engineering activities. Nizam Akbar et al. (2018) argued that even though empirical studies had been conducted, there was still no concerted attempt to address the problem that hinders Malaysia's construction industry.

CONCEPTUAL MODEL

A conceptual model is needed to assess the effect of factors using PLS-SEM. The relationships between endogenous variables and their relative exogenous variables describe this model. The conceptual model is focused on a total of 20 effects (also known as endogenous variables). Cost Effectuated Factors (CBF), Information Effectuated Factors (IBF), Human Effectuated Factors (HBF), and Government Effectuated Factors are the four types of effectuated factors (known as exogenous latent variables) (GBF).

FIGURE 1 depicts a conceptual model illustrating the relationship between endogenous and exogenous variables. PLS-SEM represents the model as two parts: (1) the measurement model or outer model, which relates exogenous factors to relative endogenous variables, and (2) the structural model, which displays the connection between various endogenous variables according to (A. Kassem et al. 2019) and shows path diagrams for each construct with descriptions of each endogenous variable (d).

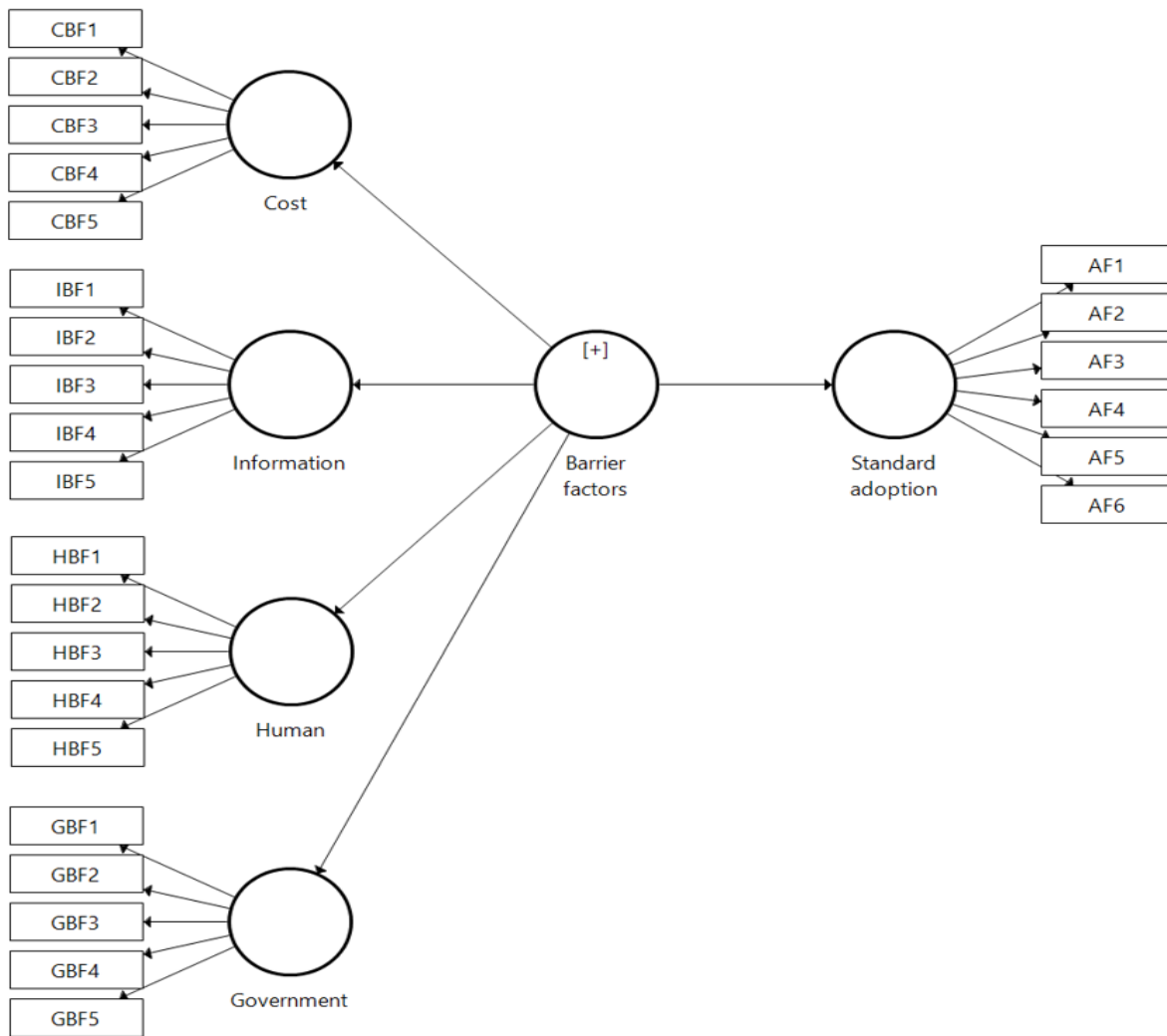


FIGURE 1. Impact of effected factors on a standard adoption relationship model using the PLS-SEM methodology

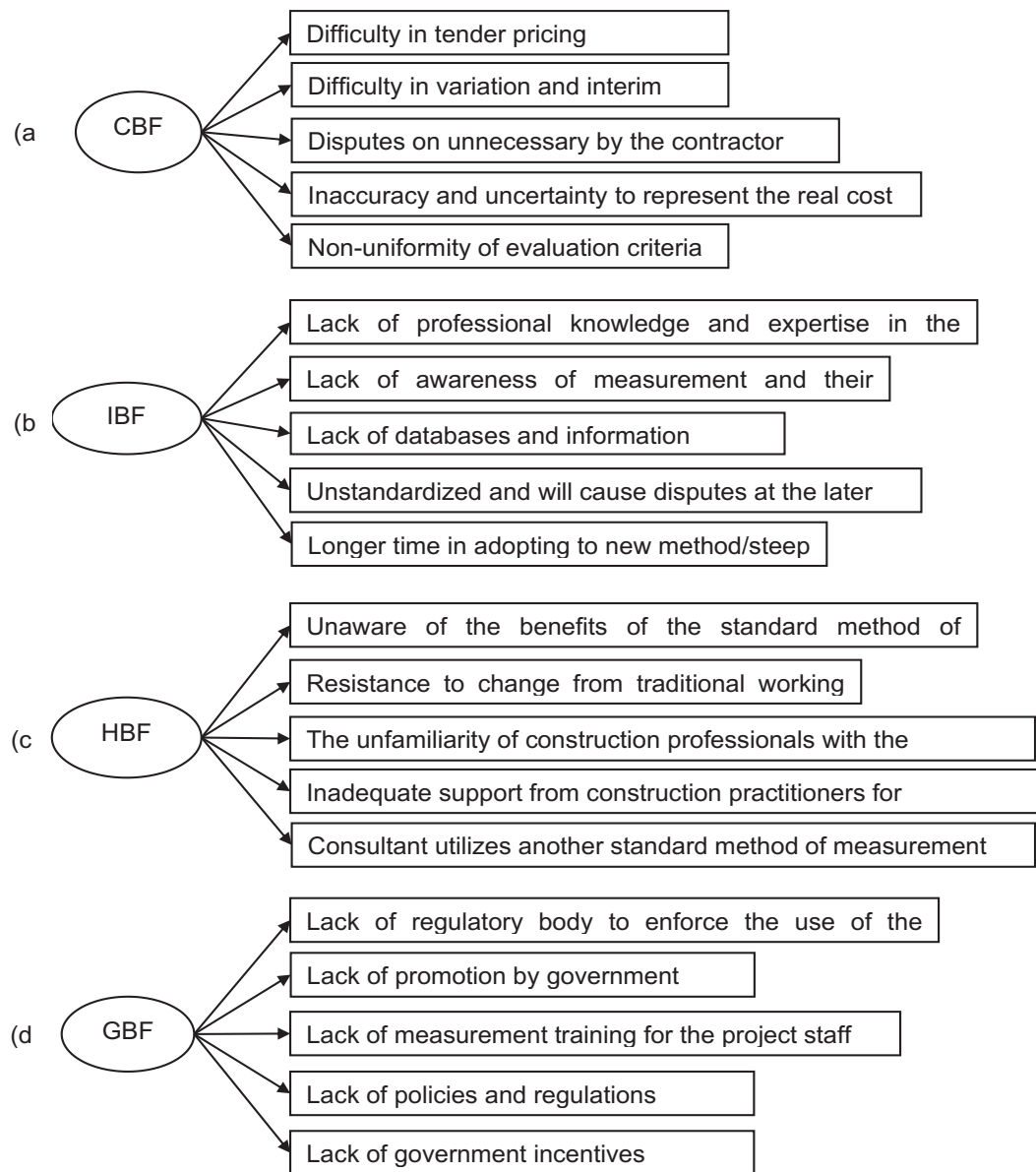


FIGURE 2. Path diagram showing the exogenous variables

DATA COLLECTION

The data collecting approach is guided by the conceptual model created before. A questionnaire survey was used to collect data for this analysis. The survey was carried out among quantity surveyor consultants in Malaysia who are involved in standard measurement methods in construction projects. In Selangor, Malaysia, 200 questionnaire forms were distributed. One hundred sixty-seven completed questionnaire sets were received as a response. Based on Hair et al. (2011)'s rule of thumb for sample size needed in PLS-SEM, the study used 167 completed questionnaire sets. TABLE shows the demographics of the respondents based on the completed questionnaire sets. Female respondents were 50.9% compared to 49.1% male respondents.

Regarding age distribution, 36.5% of respondents are between 31 and 40. The respondents between the ages of 25 and 30 are the second largest group, accounting for 35.3%, while those aged 51 to 60 account for 4.8%. From the questionnaire, 57.5% of the respondents are in the quantity surveyor position, followed by a senior quantity surveyor and assistant quantity surveyor representing 19.2%, respectively, as shown in Table 1.

The study also managed to get respondents from the top management group, namely the director of a quantity surveying firm, by 3.6% and other positions by 5.4%. In terms of construction experience, most respondents (56.9%) have more than five years of experience. The survey suggests that the survey participants are qualified, so the data gathered is considered accurate (Nizam Akbar et al. 2018).

TABLE 1. Characteristics of the respondents

Profile	Frequency	%
Gender		
Male	82	49.1
Female	85	50.9
Age		
Less 25 years	33	19.8
25 – 30 years	59	35.3
31 – 40 years	61	36.5
41 – 50 years	6	3.6
> 50 years	8	4.8
Position		
Director	6	3.6
Senior quantity surveyor	32	19.2
Quantity surveyor	88	52.7
Assistant quantity surveyor	32	19.2
Others	9	5.4
Experience		
< 5 years	72	43.1
5 – 10 years	51	30.5
11 – 20 years	33	19.8
21 – 30 years	7	4.2
> 30 years	4	2.4

DATA ANALYSIS

The conceptual model was created in SmartPLS software (Ringle et al. 2015) for simulation work evaluating the impact of exogenous variables (effected factors) on adopting the standard measurement technique. PLS is used to simulate the model by measuring and assessing validity, loading factor, and reliability tests. It requires a two-step procedure. Henseler et al. (2009) suggested that the PLS model parameters are calculated separately by solving the measurement model and then the path coefficients of a structural model (Vinzi et al. 2010).

ASSESSMENT OF MEASUREMENT MODEL

The measurement model evaluation aims to determine the accuracy and validity of the manifest variables. To assess accuracy, individual manifest and construct reliability tests are used. Individual manifest reliability measures the standardized outer loadings of the manifest variables to explain the variance of an individual manifest relative

to a latent variable (Gotz et al. 2010). Convergent and discriminant validity are used to verify variable validity (Joseph F. Hair et al. 2013). Outer loadings of 0.7 or greater on manifest variables are considered highly satisfactory. While a loading value of 0.5 is recommended, manifest variables with a loading value of less than 0.5 should be removed (Chin, 1998; Hair et al. 2010, and Hulland (1999) suggested a loading value of 0.4 as appropriate, while before removing manifest variables with loading values between 0.4 and 0.7, Henseler et al. (2009), suggested that they be checked. If removing these variables improves the composite's stability, keep them, or discard them. In this study, the cut-off value for outer loading is 0.5, and manifest variables are excluded using an iterative method based on Henseler et al. (2009).

The second criterion for consistency evaluations is constructed reliability, assessed by two measures: Cronbach's alpha and Composite Reliability (CR). Cronbach's alpha and Cronbach's CR show how well a set of manifest variables tests a single latent construct. However, as opposed to Cronbach alpha, composite durability is a superior predictor of internal accuracy since it uses uniform loadings of manifest variables (Fornell & Larcker 1981). Regardless, the understanding of the composite reliability score and Cronbach's Alpha is the same. (Litwin 1995) proposed that the value of Cronbach alpha be more significant than 0.7, and for composite durability, 0.7 is called "modest" Hair et al. (2011) and (Kassem et al. 2020).

Convergent and discriminant validities are used to assess the variables' validity. Convergent validity is determined using the Average Variance Extracted (AVE) test on variables (Fornell & Larcker 1981). Due to calculation errors, measure the amount of variance captured by a latent variable from its relative manifest variables. According to Barclay et al. (1995) and Hair et al. (2009) latent variables can absorb at least 50% of the variance from manifest variables. Therefore, the AVE value of the construct should be greater than 0.5. Suppose the cross-loading value in the latent variable is more important than that in any other construct. In that case, discriminant validity checking ensures that the manifest variable in each construct corresponds to the assigned latent variable (Chin 1998).

The measurement model is tested iteratively based on the above parameters to eliminate the weak manifest variables from the established model. Each was evaluated based on the parameters, and this analysis resulted in two manifest components discarding.

TABLE summarises the first and final iterations only. Three constructs, CRF, IRF, and GRF, have parametric measurements above the cut-off values in the first iteration of Table 2. Except for AVE, which is less than 0.5, the other construct (HRF) has achieved adequate measurement values. Following iterations, three weak manifest variables in four constructs, IRF1, HRF1, and HRF5, were discarded.

TABLE 2. Results of convergent and discriminant validity

	First iteration				Final iteration			
	Loading	Alpha	CR	AVE	Loading	Alpha	CR	AVE
CRF1	0.745	0.817	0.872	0.577	0.744	0.817	0.872	0.577
CRF2	0.726				0.726			
CRF3	0.793				0.794			
CRF4	0.810				0.811			
CRF5	0.720				0.721			
IRF1	0.593	0.773	0.845	0.524	Omitted	0.759	0.847	0.581
IRF2	0.720				0.698			
IRF3	0.790				0.767			
IRF4	0.794				0.834			
IRF5	0.705				0.744			
HRF1	0.581	0.668	0.791	0.436	Omitted	0.655	0.812	0.591
HRF2	0.729				0.789			
HRF3	0.688				0.739			
HRF4	0.760				0.776			
HRF5	0.512				Omitted			
GRF1	0.839	0.834	0.882	0.601	0.840	0.834	0.882	0.601
GRF2	0.739				0.740			
GRF3	0.728				0.727			
GRF4	0.729				0.728			
GRF5	0.833				0.833			

As shown in Table III, the final model is tested for discriminant validity based on cross-loading from the final iteration after the iteration process is completed. All variables have higher values on their relative latent variable than other constructs, as shown in

TABLE checks that each construct's manifest variables correspond to the latent variable assigned to the model's discriminant validity.

TABLE 3. Results of the cross-loading

	CRF	IRF	HRF	GRF
CRF1	0.744	0.310	0.125	0.112
CRF2	0.726	0.421	0.409	0.149
CRF3	0.794	0.403	0.324	0.396
CRF4	0.811	0.258	0.269	0.268
CRF5	0.721	0.437	0.150	0.256
IRF2	0.181	0.698	0.378	0.203
IRF3	0.422	0.767	0.270	0.208
IRF4	0.431	0.834	0.278	0.348
IRF5	0.413	0.744	0.314	0.442

continue ...

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HRF2	0.169	0.230	0.789	0.396
HRF3	0.215	0.450	0.739	0.337
HRF4	0.389	0.238	0.776	0.513
GRF1	0.219	0.362	0.368	0.840
GRF2	0.105	0.012	0.328	0.740
GRF3	0.336	0.399	0.316	0.727
GRF4	0.323	0.395	0.521	0.728
GRF5	0.208	0.289	0.546	0.833

ASSESSMENT OF STRUCTURAL MODEL

After ensuring that the measurements are correct and consistent, the next step is to evaluate the structural model's findings by evaluating the internal relationships between the endogenous variables, including examining the model's predictive capabilities and the relationships between the variables. This method consists of five steps for evaluating the structural model, as shown in Figure 3.

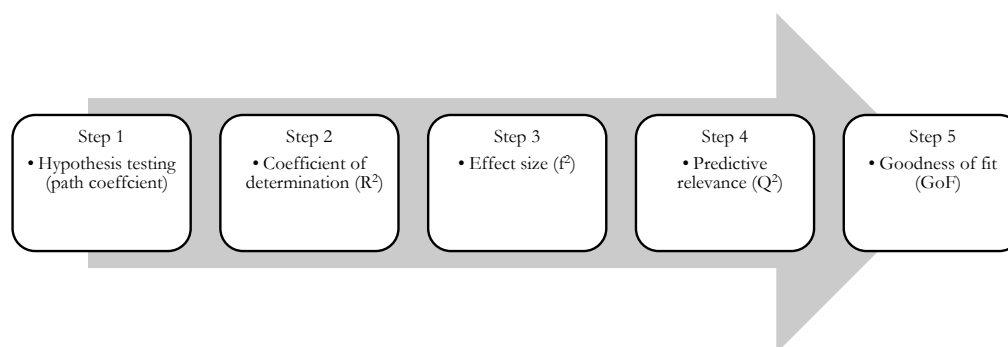


FIGURE 2. The phase of evaluating the structural model

Hypothesis testing (path coefficient)

Running the PLS method in the SmartPLS software application generates the structural model connections analysis, which is the route coefficients representing the predicted links between the components. The path coefficient limit in standardised values ranges from -1 to +1. Strong positive correlations (and vice versa for negative values) are nearly always statistically accurate when path coefficients are close to +1. On the other hand, if the computed coefficients are near zero, the link is deemed weaker, and shallow values less than zero are typically regarded as non-significant. (Hair et al. 2014).

The standard error obtained by bootstrapping determines the importance of path coefficients in general. The bootstrapping routine is used in the next phase to see if a reflective indicator contributes significantly to its corresponding objects, according to (A. Kassem et al. 2020a) while the most significant affected categories in the internal risk factors are project management factors, feasibility study-design and resources-material supply with a path

coefficient value of 0.213, 0.197 and 0.186, respectively. Moreover, for the hypotheses test, the positive relationship means that all experimental hypotheses are accepted according to path coefficient value analysis. In addition, the internal risk factors research model shows the ranking of effects on project success starting with project stoppage (loading factor 0.841). The standard bootstrap error can be used to calculate the observed t-values. If the numerical t-values are more important than the critical value, we assume the coefficient is necessary at a given probability of error (degree of significance). For two-tailed tests, the critical values are usually 1.65 (level of significance = 10%), 1.96 (level of significance = 5%), and 2.57 (level of significance = 1%). Studies in marketing usually assume a 5% degree of importance, according to (M. Sarstedt et al. 2017). According to Hair et al. (2014), the findings show that all overall effects are important at the 5% stage. In general, the area and intent of a study decide the study's significance. The path coefficient of the study hypotheses is shown in TABLE .

TABLE 4. Path coefficient of the research hypotheses

Hypothesis	Original sample (O)	t-statistics (O/STDEV)	p-values	Decision
Effectuated factors → standard measurement method adoption	0.554	10.949	0.000	Supported

Notes: *p<0.001

Coefficient of determination (R² value)

Another important criterion for assessing the PLS-SEM structural model is the R² value, also known as the determination coefficient Henseler et al. (2009). This coefficient, which is used to evaluate the model's predictive accuracy, is calculated by taking the squared variance between a given endogenous construct's actual and predicted relevance. This coefficient is calculated by squaring the variance between supplied endogenous variables' actual and anticipated values. It is used to measure the model's prediction accuracy. The R² value represents the variance ratio in the dependent variable(s) that one or more predictors can define (Elliott and Woodward 2007; Hair et al. 2014). At the same time, the optimal level of R² value differs depending on the study context (Hair et al. 2010) and (Falk & Miller 1992) both suggested a minimum reasonable level

of 0.10. Meanwhile, in PLS-SEM, R² values of 0.67, 0.33, and 0.19 are essential, moderate, and poor, respectively, according to (Chin 1998; Gotz et al. 2010), and all R² values are below 0.19 are insufficient. Table 5 displays the model's R² values.

TABLE 5. R² of the endogenous latent variables

Model strength	R ²	Result
Affected factors on the standard adoption	0.307	Moderate

Measuring the effect size (f²)

According to (J. F. Hair et al. 2014) and (Joseph F. Hair et al. 2019), When an exogenous variable is removed from the model, the difference in R² values of all endogenous

variables may be used to determine if the missing construct has a substantial influence on the endogenous variable. This measure is known as the *f*² impact scale. According to Hussain et al. (2018), the degree of impact on the endogenous variable is determined by the effect size of each exogenous variable. The determination coefficient is modified when an autonomous construct is removed from the route model (*R*²). It assesses if the deleted latent exogenous variable significantly influences the latent endogenous variable's value. The numbers fall into three categories: 0.35 (high influence), 0.15 (moderate effect), and 0.02 (weak effect) (Cohen 1988). TABLE 6 has a list of *f*² values.

TABLE 6. Effect size (*f*²) assessment

Construct	Effect size (<i>f</i> ²)	Result
Effected factors	0.443	Strong

TABLE 7. Predictive relevance (*Q*²) values

Endogenous variable	SSO	SSE	<i>Q</i> ² =(1-SSE/SSO)
Effected factors on standard adoption	1002.000	846.082	0.156

The goodness-of-fit of the model (*GoF*)

Sinesilassie et al. (2019) define model goodness-of-fit (*GoF*) as a complete model fit index that ensures that the model accurately represents the empirical data. *GoF* aims to consider the research model at both points: measurement and structural model, focusing on the model's overall performance, according to (Vinzi et al. 2010) and Sarstedt (2013). The formula for calculating *GoF* is as follows:

$$GoF = \sqrt{(R^2 * AVE^2)} \tag{1}$$

$$GoF = \sqrt{(0.307^2 * 0.537^2)}$$

$$= 0.165$$

The *GoF* conditions determine if *GoF* values are insufficient or large enough to be considered a successful validation of the PLS model (Wetzels & Oppen 2009). These conditions are listed in TABLE 8 below.

TABLE 8. Goodness-of-fit value

<i>GoF</i> Criteria	Value
Less than 0.1	No fit
Between 0.1 and 0.25	Small
Between 0.25 and 0.36	Medium
Greater than 0.36	Large

Based on Table 8, the model's result for the affected factor's effect on standard measurement adoption is 0.168, which is between 0.1 and 0.25 and is considered a small value (A. Kassem et al. 2020b) especially those related

Blindfolding and predictive relevance (*Q*²)

Hair et al. (2014) validated the blindfolding approach used to test the predictive usefulness of the route model. If the forecast is near the original value, the route model has good predictive accuracy (i.e., a small predictive error). This prediction error (defined as the difference between the actual and predicted values) is coupled with a trivial prediction error to get the value of *Q*² (defined as the mean of the remaining data) (Chin 1998) and (Marko Sarstedt et al. 2017). *Q*² values greater than zero mean that the model can predict an endogenous variable.

In contrast, values of zero and below suggest a lack of statistical significance. According to (Hussain et al. 2018), the blindfolding procedure only refers to endogenous variables with a reflective model definition and single-item endogenous variables. As shown in TABLE 7, the *Q*² criterion, suggests that the conceptual model predicts latent endogenous variables.

to the economy, politics, security and stability factors. Hence, this research aimed to investigate the fundamental relationship between the external risk factors and their effects on the construction project success using Structural Equation Modelling method and PLS-SEM approach. Design/methodology/approach— Data collected through a structured survey distributed to projects teams in the oil and gas sectors in Yemeni companies involved in mega construction projects. A hierarchal model for assessing causative external risk factors and their effects on project success was developed and analyzed using Smart PLS 3 software of SEM. Findings— The findings showed that economic, political, force majeure and security-related risk factors had a strong effect on project success. Besides, the Coefficient of Determination (*R*-squared value).

DISCUSSION

The statistical analysis revealed four effects to standard measurement method adoption, which can be divided into four categories: cost-related effected, information-related effected, human-related effected, and government-related effected. The structural equation model's findings reveal that factor loading of all items above the necessary value of 0.7 sheds light on the relationship between affected factors and standard adoption in civil engineering construction projects. All the affected factors investigated in this study play a significant role in shaping standard adoption. The survey respondents agree with these factors in terms of their effect on civil engineering projects in Malaysia.

Although the *R*² value reflects the proportion of variance in the dependent variable that one or more predictor

variables can explain, it is almost the necessary moderate value of 0.33. As a result, the researchers have come a long way toward understanding the relationship between affected factors and standard measurement adoption in Malaysian civil engineering projects. Affected factors will result in a 31% reduction in standard measuring methods in civil engineering projects.

Furthermore, the proposed model's Q^2 is 0.156 above zero, suggesting predicting endogenous latent constructs. The beta coefficient (β) value also defines the relationship frequency between exogenous and endogenous latent constructs.

TABLE shows the path coefficient of the research hypotheses test. The effected factors ($\beta=0.554$) related to standard adoption; should concentrate more on information-related effects to improve the strategy for responding to and mitigating effected, resulting in the project's cost-effectiveness.

The PLS-SEM method investigated how affected factors influence standard adoption in the Malaysian construction industry. Affected factors and their direct effect on standard adoption can be understood using this approach. In the proposed model, the hypothetical paths identified were necessary. The lack of a regulatory body to implement the standard was identified as a significant cause of standard acceptance after analysing and testing all the standardized beta coefficients in the SEM. According to the findings of the structural model, about 44.3 % of affected variables influence standard adoption in a civil engineering construction project. Cost-related factors, information-related factors, human-related factors, and government-related factors are the dominant factors that directly affect the affected factors in adopting the standard measurement, as shown in Table 2. These have a significant relationship with standard adoption. The government-related affected, which is the absence of a regulatory body to implement the standard (factor loading = 0.840) and the lack of government incentives (factor loading = 0.833), are the top five affected in terms of relative significance.

After all, since no law or regulatory body requires the use of a single standard manual for measurement work to prepare bills of quantities, this effected continues to obstruct standard method of measurement adoption (Davis et al. 2009; Davis & Baccarini 2004; Nizam Akbar et al. 2018) and (Albert et al. 2017). The effect supported a study by (Nizam Akbar et al. 2014, 2018), which said that authorities or rules did not implement the standard measurement form. Although a quantity surveyor cannot predict every situation

in construction, and measurement criteria for circumstances cannot be applicable, a quantity surveyor cannot be forced to use a specific measurement process (Shanmugapriya & Subramanian 2016). As a result, a law-governed by the government or to promote a new thing to fulfill a necessary need requires authority. The next factor is the information-related factor (factor loading = 0.834), unstandardized data that can lead to future conflicts. According to (Misnan et al. 2002), 16 % did not understand or were unaware of the primary measurement system for civil engineering works. Occasionally, consultants lack an experienced quantity surveyor who can adhere to the protocol (Srinanth et al. 2003).

Finally, inaccuracy and ambiguity of the calculated items (factor loading = 0.811) and contractor conflicts on unnecessary work (factor loading = 0.794) are cost-related factors. As a result, using a different standard measurement method would make the measured items less competitive and accurate. According to (Ahmed et al. 2018), the standard would help mitigate allegations and conflicts caused by vague definitions. It would also reduce the number of disputes and arbitration cases resulting from ambiguities in bills of quantities (Srinanth et al. 2003). The contract price will be more competitive, and the tender documents will be simpler to compare. According to (Jaggar et al. 2001), the use of bills of quantities combined with measurement rules allows for comparing all tenderers' bids on the same basis. It will reduce the possibility of tendering due to tender commonality (Ganiyu & Mohamed 2012). According to (Ahmed et al. 2018), the different measurement methods will result in project failure and impact the growth of the construction industry in Sudan. The use of various standards will result in an unequal measuring process that will prepare non-standard bills of quantities.

According to the PLS route model report, the affected factor significantly impacted standard adoption in construction projects. The R^2 value was 0.307, indicating that cost, information, human, and government effects accounted for 30.7% in standard adoption. At $t=10.949$ and $p=0.000$, the effect was directly linked to standard adoption, suggesting that effect was a significant predictor of standard adoption (see FIGURE 3). The effected factor had an effect size of 0.443 on standard adoption, suggesting that it significantly impacted the R^2 for standard adoption. The model proposed is GoF guarantees that the empirical data used to fit the model has a predictive potential of 16.5%. The model was also predictively relevant since the Q^2 value was significantly higher than zero.

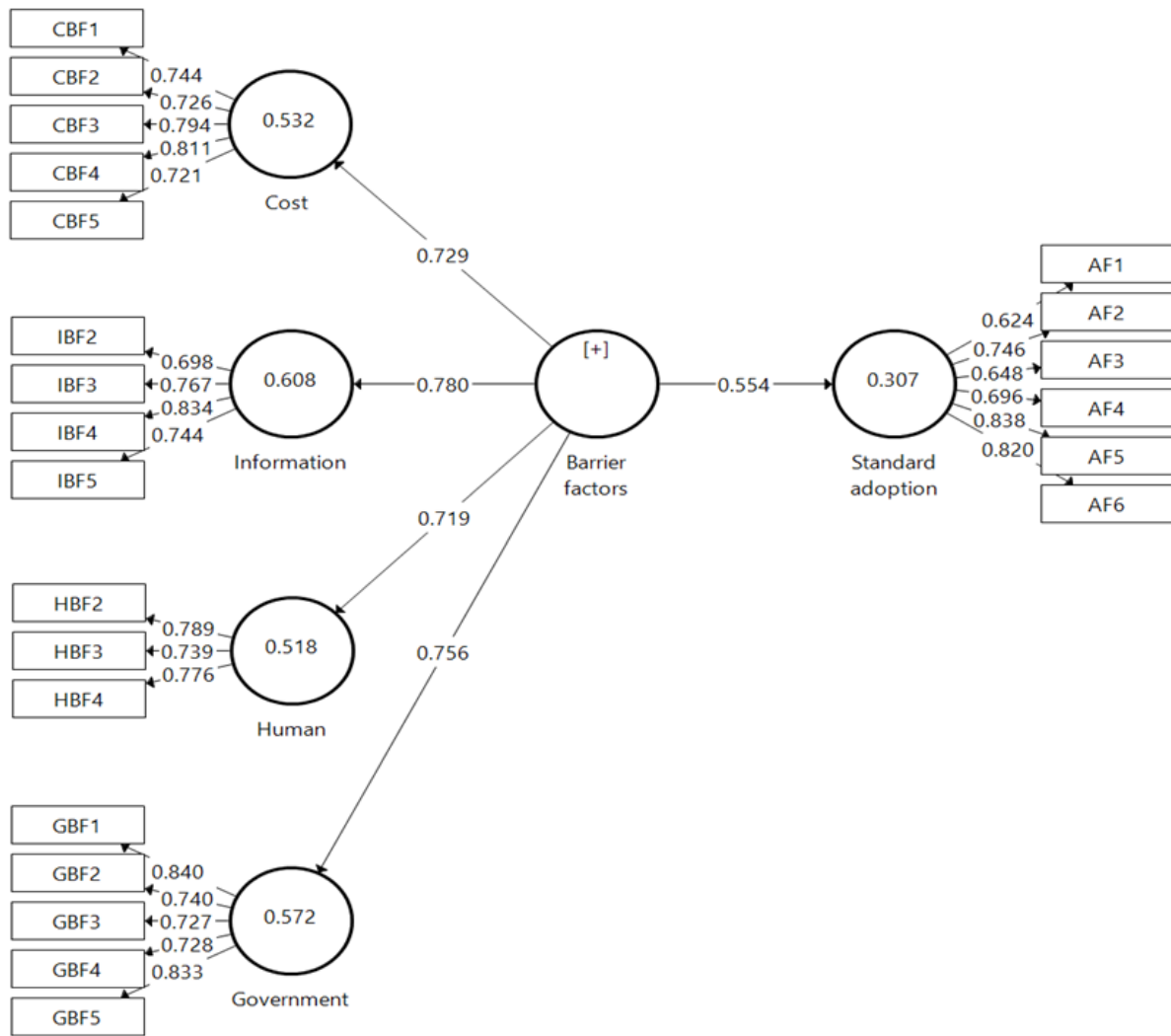


FIGURE 3. Evaluation of the structural model

The results are expected to aid construction professionals, and researchers to better understand. As a result, practitioners will be better able to make appropriate management decisions and take corrective steps in the most critical factors. The hypothesis was tested in this research, and it was confirmed that affected factors have a positive and significant relationship towards the standard adoption. As a result, affected to adoption should be addressed by developing strategies and drivers to encourage standard measurement methods in construction projects.

CONCLUSION

According to this research, several issues impede standard measurement in civil construction projects. These characteristics were categorised and modelled into four categories in the SmartPLS programme, then analysed to determine whether they influenced adoption. The following are some of the study’s key findings:

1. The investigation showed that seventeen impacted factors substantially influenced standard measurement adoption.
2. The model’s strength (R2) value is more than 0.307, suggesting a moderate model with considerable standard measurement adoption by impacted variables.
3. The impact size (f2) between influenced variables and standard measurement adoption was 0.443, demonstrating a significant link and validating the hypothesis.
4. Government-related factors are the most critical category of obstacles affecting civil engineering construction industry standards.

The study is expected to help raise awareness among construction professionals working on civil engineering projects to improve performance during the standard implementation. Besides, required strategies to respond to the adoption and to face the cost-effective in project failure.

RECOMMENDATIONS

The following recommendations for minimizing and managing affected factors in civil engineering construction projects are proposed:

Better implementation of standard measurement adoption by government and private projects reduces discrepancies in standard use between projects and contracts.

The government's or any regulatory body's standard measurement adoption compliance policies and regulations. If the usage is mandatory, all the construction players will be aware and restricted among the consultants only.

A strengthened standard measurement method research and development to avoid any discrepancies and ambiguities regarding the typical characteristics and details of the measurement.

Financial and market-based incentives for the standard method of measurement adoption from the government and financial institution loans with low-interest rates and subsidies will help the contractors and the clients benefit and perform their functions effectively.

Information on the benefits of using the standard measurement method is more readily available to encourage construction practitioners to practice and apply the standard measurement.

The institutional framework for the effective standard method of measurement implementation, especially among academia, applies and practices the measurement for the students before applying it in real construction projects.

They are raising public awareness about the standard measurement method and social media. Besides, the information can be through workshops, seminars, and conferences.

Provide a competent and proactive standard method of measurement promotion teams and local authorities.

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DECLARATION OF COMPETING INTEREST

None

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