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Knowledge Management Factors Affecting Construction Project Performance Model

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Abstract: This paper presents the development of knowledge management factors affecting to construction project performance model of UAE construction company. The data used to develop the model was collected from questionnaire survey on large construction company in UAE. The respondents were the employees of the construction company that were requested to gauge each of the knowledge management factors using 5-points Likert scale that they perceived affecting the company performance. A total of 291 valid responses were used for this analysis. After the model was constructed, it was evaluated at the measurement component of the model where it involved examining the indicator reliability, convergent validity, and discriminant validity. Then at structural component, it involved checking the strength of the relationship, checking coefficient of determination, conduct predictive relevance of the model, calculate goodness-of-fit (GOF) and conduct hypotheses testing. It was found that two out of four constructs are significant which are having t-value above the cut-off value of 1.96. The significant relationships are knowledge management technology (KMT) and knowledge management process (KMP) toward project performance. These outcomes are from actual perception from the respondents where the collected data is not strong enough to trigger the significant relationship of other constructs that had been hypothesised. The model can help to give better understand to parties that concerned the knowledge management in construction industry.

Keywords: Knowledge management, construction project performance

1. Introduction

Knowledge has a significant influence on both of the actions an organisation takes and the decisions it makes. As a result, the efficiency of knowledge management is inextricably linked to the achievement of an organisation's objectives. This helps to explain why organisations are increasingly investing in knowledge asset management. Among the most common reasons cited for such investments are enhancing the organisation's capacities, fostering performance effectiveness, and increasing decision making via strategic application of knowledge assets. These knowledge assets may perhaps be explored independently or as the knowledge management system as a concept (Yeong, 2010). In project management aspect, a critical success factors are a list of areas or a collection of variables that a project manager should be well-versed in in order to produce a successful project (Verburg et al., 2013). Fortune and White (2006) outlined a list of critical success factors that knowledge management activities could potentially affect, including:

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i. Support from senior management;
ii. a capable project manager;
iii. skilled and trained staff/training provision;
iv. learning from previous experience;
v. departmental understanding;
vi. good communication/feedback;
vii. organisational adaptation/culture/structure;
viii. user/client involvement;
ix. consultant involvement

Current scenario of construction companies in the UAE indicates that firms should prepare ahead for knowledge management implementation by encouraging the use of technology like online applications and social media platforms for information sharing. Human resource departments, not just information technology departments, should be involved. In order to assist construction firms, it is essential to have a clear understanding of the challenges to knowledge management implementation. The number of studies of knowledge management in construction companies in the UAE are very limited, but Ghabbour (2017) provided different barriers of construction firms in the UAE, which are summarized as follows:

i. The nature of construction project in the UAE and lack of post projects reviews and documentation;
ii. Resources required in terms of budget, staff and information technology infrastructure; lack of time to participate in knowledge management activities;
iii. Top management doesn't fully support implementation of knowledge management system by developing required processes and written knowledge management strategy,
iv. Organization cultural doesn't fully support introducing new ideas and technologies.

These obstacles and barriers negatively impact knowledge management in the UAE which necessitates a more formal approach to resources and techniques for using knowledge in the construction industry. Planning, managing project, expense and time overruns, and non-achievement have often been central issues with project management activities (Alias et al., 2014). In the UAE, there is a scarcity of empirical data to back up related best project management practises. Thus, there is a need for a deeper understanding of the underlying mechanisms for project management activities that could lead to effective results. As a result, the current study is an attempt to identify the knowledge management factors that affect construction project management performance in the context of construction firms in the UAE. The knowledge management factors are as in table 1.

Table 1 - List of knowledge management factors

Code	1. Knowledge Leadership [KML]
KML1	Organisation encourages team members to participate in project knowledge management activities.
KML2	Organisation supports team members to participate in project knowledge management activities.
KML3	Provide necessary help and resources to participate in project knowledge management activities.
KML4	Are keen to see that the employees happy to participate in project knowledge management activities.
KML5	Has sufficient resources in project knowledge management activities.
KML6	Has sufficient financial resources for building an ICT system to manage project knowledge.
KML7	Has sufficient skilled project team members to perform project knowledge management activities.
KML8	Provides time for project team members to perform project knowledge management activities.
	2. Knowledge Culture [KMC]
KMC1	Provides tangible incentives to encourage participation in project knowledge management activities.
KMC2	Motivates employees to participate in project knowledge management activities.
KMC3	Rewards employees who create, share, store and use knowledge to perform projects.
KMC4	Having reward system to encourage more group to participate
KMC5	Values knowledge seeking and problem-solving.
KMC6	Has a high level of trust among employees for sharing project knowledge
KMC7	Encourages project team members to share mistakes about projects openly without the fear.
KMC8	Encourages collaboration among project team members.
	3. Knowledge Processes [KMP]
KMP1	Provide training/instruction as normal work practices to project team members.
KMP2	Processes for sharing lessons learned are widely accepted as part of normal work practices.
KMP3	Processes for documenting lessons learned are regularly improved and updated.
KMP4	Processes for searching for lessons learned are regularly improved and updated.
KMP5	Ability to provide knowledge that others need.

KMP6	Provide valuable knowledge for carrying out projects.
KMP7	Believe in sharing knowledge with others.
KMP8	Believe that most other employees can provide more valuable knowledge
	4. Knowledge Technology [KMT]
KMT1	Make use of technology to access knowledge in performing projects.
KMT2	Use project knowledge networks to communicate with others.
KMT3	Use technologies that allow them to share knowledge about projects within the organisation.
KMT4	Use technologies that allow to share knowledge about projects with others outside the organisation.
KMT5	Participate in knowledge management technology activities such as searching, creating and others.
KMT6	Actively share the project knowledge with others using available technology.
KMT7	Encourage other project team members to apply knowledge technology
KMT8	Responsible for creating project knowledge-sharing technology environment.

Hence, this paper established a structural PLS-SEM model of knowledge management factors as the above table 1 that influence/affecting construction project efficiency performance of a company.

2. Model Description

The development of the model is based on Structural Equation Modelling (SEM) of Partial Least Square (PLS) technique. Fundamentally, there are two techniques for conducting SEM which are Partial Least Squares Structural Equation Modelling (PLS-SEM) and Covariance-Based Structural Equation Modelling (CB-SEM). PLS technique was selected because it is meant for theory prediction and development. While CB-SEM technique is use for theory testing and confirmation (Hair et al., 2017). The model is conceptualised according to causes and effects relationships. It is comprised of 32 knowledge management factors affecting the construction project performance. These factors were clustered into four groups namely knowledge management leadership, knowledge management culture, knowledge management process and knowledge management technology. The four knowledge management factors' groups formed as exogenous/independent constructs of the model and the only endogenous construct is construction project performance. The hypotheses for this model are as in table 2.

Table 2 - Hypothesis of the model

Code	Hypotheses
H1	Knowledge Management leadership has significant effect on project performance
H2	Knowledge Management Culture has significant effect on project performance
H3	Knowledge Management Process has significant effect on project performance
H4	Knowledge Management Technology has significant effect on project performance

The characteristics of the models' constructs and variables/indicators of the model are as in table 3:

Table 3 - Model's construct and variables/factors/indicators

Constructs	Name	Code	Numbers factors/indicators
Exogenous	Knowledge Management leadership	KML	8
	Knowledge Management Culture	KMC	8
	Knowledge Management Process	KMP	8
	Knowledge Management Technology	KMT	8
Endogenous	Project performance		3

The data used to develop the model was derived from a questionnaire survey where the respondents were the construction practitioners. The respondents were requested to gauge each of the knowledge management factors using 5-points Likert scale that affect the company performance. In the questionnaire survey, a total of 350 questionnaire sets that were distributed and only 291 valid returned questionnaire which represent 83% response rate were used in this modelling analysis work. The collected data was prepared in MS Excel worksheet and then saved as *comma delimited* (*CSV*) type and then uploaded in the SmartPLS software for constructing and evaluating the model as figure 1.

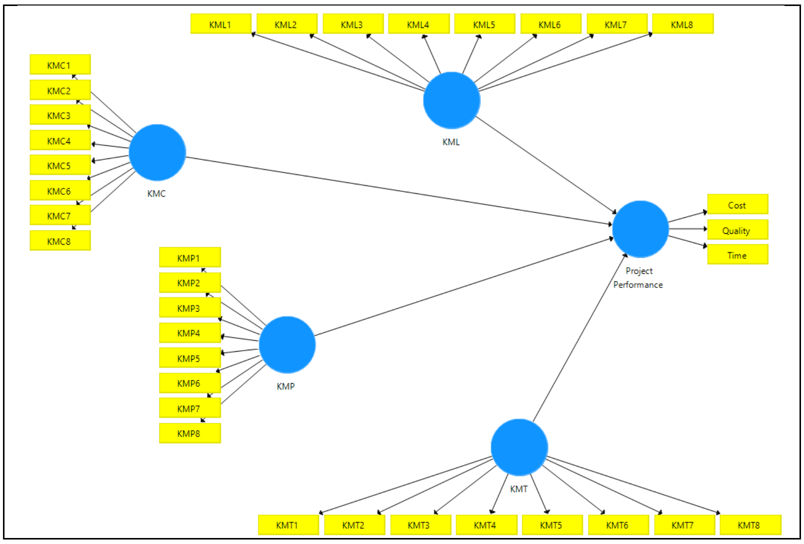

Fig. 1 - The developed model

Figure 1 demonstrates the skeleton of the constructed model in the drawing board of SmartPLS software. The shape of the model is categorised as reflective model because paths of the indicators are in outward direction from the constructs (Hair *et al.*, 2017). Hence, model evaluation was conducted according to the processes and regulations which comply with reflective model specification. Evaluation of the model is carried out in two phases where the first phase is evaluation at measurement component and the second phase is at structural component of the model is as follow.

3. Measurement Assessment

The measurement model is assessed based evaluation criterions for measurement and structural model. At the measurement model, the assessment involved by examining the indicator reliability, convergent validity, and discriminant validity.

3.1 Indicator Reliability

Once the model has been constructed, the processes started by conducting iteration on the model using ***PLS Algorithm*** function to calculate the model criteria's estimates. The assessment of the indicator reliability depends on examining the factor loading values. The modelling evaluation is carried out by consecutive iterations and deletion of item/variable. At the second iteration/modelling, the model has achieved indicator reliability and the generated values of indicator reliability above the criteria threshold values are as displayed in table 4.

Table 4 - Indicator reliability

Items / variables	KMC	KML	KMP	KMT	Project Performance
Cost					0.945
Quality					0.897
Time					0.955
KMC1	0.714				
KMC2	0.814				
KMC3	0.859				
KMC4	0.822				
KMC5	0.932				
KMC6	0.868				
KMC7	0.886				
KMC8	0.896				
KML6		0.888			
KML7		0.958			
KML8		0.924			
KMP1			0.88		
KMP2			0.883		
KMP3			0.85		
KMP4			0.879		
KMP5			0.844		

KMP6	0.869	
KMP7	0.803	
KMP8	0.798	
KMT2		0.719
KMT3		0.837
KMT4		0.89
KMT5		0.927
KMT6		0.92
KMT7		0.889
KMT8		0.832

Table 4 indicates that all the left-over indicators/variables in the model are having factor loading equal or more than 0.5 which is above cut off value for the factor loading.

3.2 Convergent Validity

The convergent validity is assessed by examining the construct reliability include Cronbach's alpha (α) and Composite Reliability (CR) must be greater than or equal to 0.70, and Average Variance Extracted (AVE) should greater than 0.50. Then for convergent validity of the constructs of the model, the values are as presented in table 5.

Table 5 - Convergent validity values

Constructs	Cronbach's Alpha α	Composite Reliability (CR)	Average Variance Extracted (AVE)
KMC	0.946	0.954	0.725
KML	0.914	0.946	0.853
KMP	0.946	0.955	0.725
KMT	0.942	0.952	0.742
Project Performance	0.925	0.952	0.87

Table 5 shows all the values are above the threshold criteria. Where the Cronbach's alpha (α) and Composite Reliability (CR) for all constructs are above 0.70 and the Average Variance Extracted (AVE) values are more than the cut-off value of 0.5. Hence, the evaluation of the indicator reliability and convergent validity values of the measurement model are above the criteria cut-off values.

3.3 Discriminant Validity

Discriminant validity can be carried out in two approaches which are cross-loading technique and Fornell-Larcker criterion technique. Cross-loading technique makes comparisons between the AVE square root values with the latent variable correlation value. Thus, this study accepted Fornell–Larcker and cross-loading criterion in inspecting the discriminant validity of the measurement model. Finally, the square root of AVE value of the model reached the adequacy of discriminant validity criterion as in Table 6.

Table 6 - Fornell-Lacker criterion

Constructs	KMC	KML	KMP	KMT	Project Performance
KMC	**0.851**				
KML	0.447	**0.924**			
KMP	0.758	0.265	**0.851**		
KMT	0.305	0.08	0.44	**0.862**	
Project Performance	0.226	0.06	0.277	0.84	**0.932**

Table 6 represent the bolded square root of AVE and non-bolded values represent the inter-correlations value between constructs. It is indicated that all off-diagonal elements are lower than square roots of AVE. Hence, confirming that the model had achieved criterion of discriminant validity. The results of cross loadings for the measurement model are as shown in Table 7.

Table 7 - Results of indicators cross loadings

Factors	KMC	KML	KMP	KMT	Project Performance
Cost	0.192	0.062	0.249	0.819	**0.945**
KMC1	**0.714**	0.536	0.468	0.154	0.099

KMC2	**0.814**	0.54	0.493	0.236	0.202
KMC3	**0.859**	0.411	0.575	0.224	0.145
KMC4	**0.822**	0.342	0.565	0.211	0.149
KMC5	**0.932**	0.391	0.683	0.248	0.18
KMC6	**0.868**	0.317	0.647	0.221	0.182
KMC7	**0.886**	0.316	0.757	0.33	0.229
KMC8	**0.896**	0.321	0.826	0.354	0.265
KML6	0.357	**0.888**	0.213	0.081	0.046
KML7	0.397	**0.958**	0.232	0.074	0.064
KML8	0.484	**0.924**	0.292	0.069	0.054
KMP1	0.854	0.299	**0.88**	0.373	0.241
KMP2	0.793	0.286	**0.883**	0.37	0.265
KMP3	0.675	0.2	**0.85**	0.299	0.171
KMP4	0.687	0.246	**0.879**	0.326	0.147
KMP5	0.617	0.26	**0.844**	0.366	0.181
KMP6	0.58	0.212	**0.869**	0.352	0.213
KMP7	0.484	0.158	**0.803**	0.377	0.238
KMP8	0.494	0.16	**0.798**	0.452	0.322
KMT2	0.344	0.105	0.54	**0.719**	0.472
KMT3	0.345	0.093	0.485	**0.837**	0.598
KMT4	0.333	0.092	0.474	**0.89**	0.666
KMT5	0.298	0.11	0.404	**0.927**	0.777
KMT6	0.274	0.059	0.345	**0.92**	0.865
KMT7	0.181	0.041	0.295	**0.889**	0.835
KMT8	0.141	0.009	0.238	**0.832**	0.735
Quality	0.237	0.043	0.274	0.746	**0.897**
Time	0.205	0.061	0.254	0.782	**0.955**

Table 7 shows that the cross-loading values of each indicator within its latent construct are higher (as signified with bold font) as compared with values to other latent constructs of the model. Each item outer loading is greater than its value in the other constructs. It demonstrates that the discriminant validity of model is attained. Hence, it can be concluded that the measurement model had achieved model goodness-of-fit criteria and the final model is as figure 2.

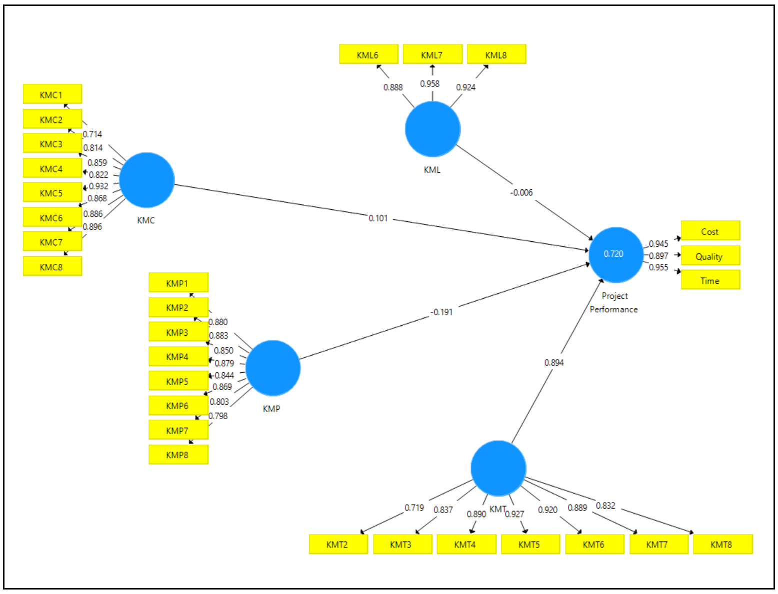

Fig. 2 - Final model

4. Structural Assessment

The assessment involved the following inspections (Rahman, I.A. et.al 2022);

i. Path relationship strength
ii. Coefficient of determination
iii. Predictive relevance of the model
iv. Goodness-of-fit (GoF)
v. Hypotheses of the paths

4.1 Path Relationship Strength

According to Hair *et al.* (2019), path coefficients is measured with beta (β) value that reflect is the strength of the path or relationship between exogenous and endogenous constructs with values approximately between –1 and +1 (values can be smaller/larger but usually fall in between these bounds). Path coefficients values close to +1 represent strong positive relationships and vice versa for negative values that are usually statistically significant. The closer the estimated coefficients are to 0, the weaker are the relationships. The generated path coefficients or beta values of the model are extracted from the software and tabulated as in table 8:

Table 8 - Beta values of the paths

Independent constructs	Project Performance [Beta values]	Remarks
KMC	0.101	Rank 3
KML	-0.006	Rank 4
KMP	-0.191	Rank 2
KMT	0.894	Rank 1

Table 8 shows that beta values of four relationships. According to Hair et al. (2017), β value should be above 0.1 regardless its signage either positive or negative. Thus, knowledge management technology (KMT) construct is having the strongest while knowledge management leadership (KML) construct is the weakest relationship to the project performance construct.

4.2 Coefficient of Determination

Coefficient of determination is also known as R2 which can be viewed as the combined effect of the exogenous variables on endogenous variables of the model. The R2 values ranges from 0 to 1 with value closer to 1 representing complete predictive accuracy. This study adopted the R2 threshold value by Cohen (1988) which R2 value of 0.26 is considered as substantial, R2 value of 0.13 is regarded as moderate, and R2 value of 0.02 is considered as weak. The R2 value for this model is extracted from the final model generation using PLS Algorithm function in SmartPLS software which is equal to 0.720 and considered as substantial effect.

4.3 Predictive Relevance of The Model

Predictive relevance is by measuring (q2) index where it is founded on Q2 values that quantify the variances between the omitted and the predicated data points (Chin, 1998; Tenenhaus et al., 2005). By applying the blindfolding iteration process, the Q2 values can be generated which are used to calculate predictive relevance (q2) as suggested by Cohen (1988) suing the following equation;

$$q^2 = \frac{Q^2_{included} - Q^2_{excluded}}{1 - Q^2_{included}} \qquad (5.2)$$

where;

q^2 = predictive relevance
Q^2_{included} = value of the endogenous latent variable where all the exogenous construct variables are included in the model
Q^2_{excluded} = a selected exogenous construct is excluded from the model

In the blindfolding process, each construct is deleted to generate Q^2_{excluded} value for calculating q^2 value. This iteration process was then repeated to each of exogenous constructs until finished. According to Cohen, (1988) as the rule of thumb, it states that if the q^2 value is equal and more than 0.02 but less than 0.15 then it indicates that the respective exogenous construct is having small predictive relevance, for q^2 value is equal or more than 0.15 but less than 0.35, it indicates that the respective exogenous construct is having medium predictive relevance, for q^2 value is equal and more than 0.35 then it indicates that the respective exogenous construct is having large predictive relevance (Hair *et al.*, 2017). The predictive relevance values for this study's model are as in table 9.

Table 9 - Predictive relevance (q2)

Exogenous construct	Calculated (q^2) values	Status
KMC	0.056	Small
KML	0.003	Small
KMP	0.078	Small
KMT	0.673	Large relevancy

The results in table 9, indicate that only knowledge management technology (KMT) construct is having predictive relevance with q^2 values of 0.673. This means that the construct has large predictive relevancy however others construct have small predictive relevancy to the structural model. This is resulted from the collected data that is not strong enough to trigger the predictive relevancy of the endogenous construct data to exogenous construct data.

4.4 Goodness-of-Fit (GoF)

GoF index is for assessing the global validity of a model. It is the geometric mean of the average communality (AVE) and the average coefficients of determination (R^2) value of the model (Hair, Ringle & Sarstedt, 2011). The GoF value of the model should be in the range between 0 and 1. If the value is equal or more than 0.1 but less than 0.25, the model can be categorised as having small validating power; if the GoF value is equal or more than 0.25 but less than 0.36 then it can be categorised as having medium validating power and for GoF value equal or more than 0.36, the model is considered having high/large validating power (Wetzels *et al.*, 2009; Akter *et al.*, 2011; Hauashdh et al., 2022). Hence, GoF index of a model can be calculated manually using the following formula:

$$GoF = \sqrt{\overline{AVE} \times \bar{R}^2} \quad (1)$$

where;

GoF = goodness-of-fit
AVE = average communality
R^2 = coefficients of determination

Hence, for this model the average of AVE for the entire construct variable and the R^2 for all dependent constructs variables as in Table 10.

Table 10 - Calculation of GoF

Constructs	AVE [construct validity]	R^2 values
KMC	0.725	
KML	0.853	
KMP	0.725	0.720
KMT	0.742	
Project Performance	0.87	
Average	0.783	

The average of AVE for endogenous variable is 0.783 and the average R^2 for all dependent variables is 0.720. Thus, the calculated, $GoF = \sqrt{0.783 \times 0.72}$ = 0.75084. This indicates that the model is having global large/high validating power.

4.5 Hypothesis Testing

Hypothesis testing for this model is conducted using bootstrapping function of the SmartPLS software. The bootstrapping method is basically the derivation of the sample from the sample (Civelek, 2018). In this procedure, a large number of 5000 resamples are taken from the original sample with replacement to give bootstrap standard errors, which in turn gives approximate T-values for significance testing of the structural path (Hauser, Ellsworth, & Gonzalez, 2018). The generated t-values and p-values for the hypothesis testing for this study's model are shown in Table 11.

Table 11 - Results of bootstrapping

Hypothesis	T Statistics (≥1.96)	Remark
KMC -> Project Performance	1.955	Not significant
KML -> Project Performance	0.184	Not Significant
KMP -> Project Performance	4.015	Significant
KMT -> Project Performance	50.959	Significant

The hypothesis testing results show that two out of four constructs are significant which are having t-value above the cut-off value of 1.96. The significant relationships knowledge management technology (KMT) and knowledge management process (KMP) toward project performance. Unfortunately, the other three exogenous constructs are not significant and this is due to the characteristics of the collected data which is not strong enough to establish significant relationship as what been hypothesized.

5. Conclusion

This paper has discussed the construction and assessment of PLS-SEM model on the relationship between fours knowledge management dimensions with the construction project performance. The model adopted partial least square (PLS) approach of structural equation modelling (SEM) and developed in SmartPLS software. The model was evaluated at measurement level/component and then at structural level/component. The result of the evaluation found that the model has achieved its goodness-of-fit criteria. The fit model was checked for hypothesis testing using bootstrapping function of the software and found that two out of four constructs are significant which are having t-value above the cut-off value of 1.96. The significant relationships knowledge management technology (KMT) and knowledge management process (KMP) toward project performance. This happened could be due to actual perception from the respondents or the collected data is not strong enough to trigger the significant relationship that had been hypothesised.

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