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Knowledge Management Mediation Model of Higher Learning Institution Performance

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Abstract: There are many studies on Knowledge Management (KM) in different organizations however less investigation on university, especially teaching staff in terms of using KM to enhance their duties at the universities. Thus, this paper presents a study to examine the Critical Influential Factors of Knowledge Management and Innovation Management on UAE Universities Performance. The study adopted a quantitative approach where a questionnaire survey was carried out among academic staffs of UAE universities. A total of 330 respondents involved in this survey. The data gathered from the survey was used to develop the mediation model which comprises of innovation learning acts as mediator to the relationship between the five knowledge management variables and the university performance variable. The model was developed and assessed in SmartPLS software. The mediation model comprises of direct effect relationship and mediation effect relationship. For direct effect relationship, it was found that two KM dimensions have a direct significant effect on universities' performance, which are knowledge acquisition and knowledge application. And also, it indicates that there is a significant direct effect for innovation learning on university performance. For mediation effect, it was found that innovation learning on the relationship between KM dimensions (knowledge acquisition, knowledge storage, knowledge sharing, and knowledge application) and universities' performance. The results from this modelling work, indicated that knowledge acquisition and knowledge sharing have a significant indirect effect on universities' performance with partial mediation for knowledge acquisition and full mediation for knowledge sharing. The findings of this research could benefit academic and decision makers in terms of enhancing organization performance through KM. Also, innovation learning can be considered as a stimulant to KM in further enhancing the university organization performance.

Keywords: Knowledge management, innovation learning,university performance

1. Introduction

Knowledge, not just the data or details and the use of knowledge are commonly recognised as important tools for constant growth and the key to sustained competitive advantage (Alhussain 2011; Iqbal et al., 2019), particularly when circumstances are complicated and unpredictable (Harorimana Mr 2010; Mahdi, Almsafir& Yao 2011; Moghaddam, Mosakhani & Aalabeiki 2013, Abubakar et al. 2019). Undeniably, the business world has transited to the knowledge worker era where employees are major determinant of business performance, and sustainability (Salahudin et al, 2019).

It is undeniably important to learn how to address the importance of information of better corporate competence within the ever-changing environment of rising global competitiveness (Allameh&Zare 2011; Mahdi, Almsafir& Yao 2011). There is no exaggeration to say what consumers know, how they use what they know and how soon they are to know something different provides an enduring market benefit in today's information intense climate (Abebe &Onyisi 2016; Urbancova 2013; Li et al, 2020).

Knowledge management is one of the contemporary administrative concepts in which literature has grown in quantity and quality. The past years have witnessed a growing interest in the part of organizations towards adopting a concept of knowledge management (Li et al, 2020). Knowledge in terms of efficient engagement and dialogue between individuals and communities is also integrated with IT, and transnational leadership must be invested by organisations that embody leadership and organisational culture in order to get benefit of knowledge to enhance their organizations (Albassami et al, 2019). These organizations have participated in laying the foundations for knowledge management, with much emphasis given to the technological, social and organizational aspects (Novak et al, 2020).

There is a relative lack of empirical data and theory to guide the concept, cultivation and sharing of knowledge (Buafra et al, 2021). As such, knowledge management is becoming increasingly important in light of the major challenges that organizations face. This is reinforced by the ever-increasing importance of cognitive objectives that focus on knowledge management, and therefore, leading to enhanced productivity, efficiency and effectiveness in any organization (Burton, 1999, Santoro et al, 2018). In order to achieve the desired benefit of adopting the knowledge management approach in organizations, the role of the organization's management should focus on the effective use of this approach and employing it towards attaining the strategic goals and operational objectives of the organizations, thus, enhancing the organization's various capabilities and skills towards achieving development, improvement and sustainability of its' capacities and skills (Sadq et al, 2020). Additionally, knowledge management also lead to higher innovation in organizations (Buafra et al. 2021), therefore the management of the organization should focus on directing knowledge management processes towards institutionalization. Emphasis should be placed on the implementation of a knowledge strategy that ensures that knowledge management operations across all units are effectively integrated. (Bhatt, 2001, Xu et al, 2018).The concept of knowledge management dates back to Don Marchand in the early 1980s, as the final episode in a chain of assumptions related to the evolution of information systems. McDermott (2001) also predicted that the model work would be knowledge-based and that organizations would be made up of knowledge workers who direct their performance by feeding back to their colleagues and customers.

Certain commentators trace knowledge management back to 1985, when Hewlett Packard Corporate applied the term. However, during that period, many were not convinced of knowledge management and its impact on business. Even Wall Street, "the world's largest money market", initially ignored knowledge management especially attempts to determine the monetary value of knowledge. During the twentieth century, practical and academic attentions have been paid to the notion of organizational knowledge management. This interest has been increasing in recent years, after many organizations have adopted it globally. In 1999, the World Bank allocated 4% of its annual budget to develop knowledge management systems. In recent decades knowledge management (KM) has proven itself to be a modern discipline that attracts a growing research population worldwide and not a fashionable research phenomenon. A new and influential methodology in the management science has been considered. KM is a new source of sustainable competitive advantage which redefines business strategies for organisations all over the world. Research demonstrates that KM is a history and the base for organisational creativity (Chen et al., 2010). Established literature notes that KM systems, including development, procurement, distribution, usage (Chen et al., 2010), include supervisory, management, policies, correspondence, knowledge security, strategy KM, knowledge-based learning, recruiting, performance evaluations, rewards, learning system, information technology, etc. practise; (Henri TapioInkinen, Aino Kianto, Mika Vanhala, 2015).

Menor et al., (2007) and Aramburu & Saenz (2011) have creative consequences, on the other hand, for knowledge-based assets such as man, institutional and relational capital. However, there are only a few empirical studies based on the relationship between KM and innovation in academic circles, especially in institutions of higher education. This research wants to provide objective proof of how KM drives creativity in UAE public universities to address this void in current literature. The objective of this study is to enhance the awareness of HEIs in terms of improving their operational innovation through KM activities. Further, the research adds to the literature on KM and innovation management by explore the influence of KM on UAE HEI innovation. The research presents the theoretical principles of KM and creativity, and examines empirically the correlation with 2 innovation components, including administrative and technological development, with three KM components, including information accumulation, knowledge dissemination and the usage of knowledge.

2. Related Researches on Knowledge Management

A study conducted by Biyagautane & Al-Yahya, (2011) has investigated the importance of creating, capturing, documenting and disseminating knowledge within organizations in UAE. Another study by Hussain et al. (2015) which determined the attributes of knowledge management on small and large manufacturing firms' competitive priorities in the UAE. These two studies determined the importance of KM to public organizations and the effects of its attributes on competitive priorities of manufacturing firms respectively, all in the UAE. The studies used analytical hierarchical process method to analyse the data. The results show positive relations between the variables. However, the studies did not investigate the effects of KM process (knowledge acquisition, creation, dissemination, storage and knowledge protection) on organization competitiveness through innovation and learning.

In another study conducted by Whee, Ngah & Seng (2012) has investigated the impact of knowledge management capability that made-up of knowledge infrastructure capability and knowledge process capability on learning organization performance of UAE universities. The research shows the various KM capabilities within an organization that when harnessed will influence firm performance. another study by Alsalim& Mohamed (2013) indicated that the relationship between KM processes (knowledge generation, storage, dissemination and application) and organizational performance in Iraqi's colleges in the Institute of Technical learning to be positive and significant. It further indicated that KM operations impacted greatly on organizational performance indicators. The methods used for data collection and analysis were questionnaire and correlation regression. However, the study was not conducted on UAEs' universities and the dependent variable was not firm competitiveness.

Another study conducted by Abdallah, Khalil & Divine (2012) investigated the impact of knowledge sharing (individual, organizational and technological factors) on innovation capability in organizations within UAE. The findings show a significant positive correlation between variables, however, there are variations in the degree of correlation among the independent variables. ICT is having the strongest relationship with innovation capabilities in organization. The study was not conducted on public sector and it did not measure KM processes on competitiveness in UAE. Again, research on the influence of KM process on organizational business processes was carried out by Hegazy&Gorab (2014). Specifically, they investigated the effect of knowledge discovery, knowledge capture, knowledge sharing and knowledge application on business processes' effectiveness, efficiency, and innovation; and employees' learning, adaptability, and job satisfaction. The result indicated that KM process significantly influence business processes' effectiveness, efficiency, and innovation positively which eventually led to employee job satisfaction. However, the study was not conducted on the effect of KM process on organizational competitiveness through innovation and learning.

Related studies conducted on the effect or influence of KM process on organizations performance and business process effectiveness are very few in the UAE. However, there are studies like that of Chang & Lee (2007) empirically tested the effect of KM processes (knowledge acquisition, knowledge storage, and knowledge diffusion) on organizational innovation. Liu & Tsai (2007) found that KM process (knowledge acquisition, knowledge creation, knowledge storage and knowledge sharing) through KM system positively enhance organizational operating performance. Similarly, Jiang & Lia (2008) established the effects of knowledge sharing and knowledge creation on firms' innovative performance.

Other researches on the impact of knowledge application are few as well, people like Liu (2003) study discovered that knowledge application as a dimension of KM system explored improves individual learning in the organization. In the same vein, Al-Busaidi (2005) investigated and the result indicated that knowledge utilization results in individual benefits, which was assessed by measurements related to effectiveness, efficiency, innovation and learning. Again, study by Jennex & Olfman (2006) found that the application of KM system led to an improved individual productivity as regards decision making, origin cause analysis, problem resolution, timeliness, and operability assessment documentation, they were found to have improved individual productivity which led to organizational productivity. Toe and Men (2008) study was in the area of knowledge portal, the findings show that utilization of knowledge portal increases firms' performance. Similarly on the context of KM portal, De Carvalho et al. (2007) discovery was that usage of enterprise portal build and encourage sense making, knowledge creation and decision making.

From the reviewed work on KM and other factors, none of the studies used KM processes on organizational competitiveness through innovation and learning in the public sector of UAE. This study therefore intends to cover this gap by conducting research in the aforementioned area, using KM processes (Knowledge creation, Knowledge sharing, Knowledge storage and Knowledge application) as independent variables. The dependent variable remained organizational competitiveness and the mediating variable is innovation learning. The hypothetical model for this study is as figure 1.

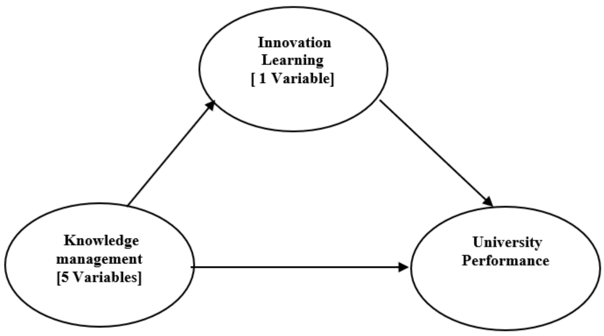

Fig. 1 - Hypothetical model

Figure 1 shows the hypothetical model that describe the relationship between the independent variable, dependent variable and also mediation variable. These variables are as in table 1.

Table 1 - Variables and factors for the model

Independent variables with factors	Mediation variable with factors	Dependent variable with factors
Acquisition [7 factors] Storage [7 factors] Sharing [6 factors] Application [7 factors]	Innovation [7 factors]	University performance [11 factors]

These variables together with the factors were used in the main content of the designed questionnaire for this study. The respondents were requested to gauge each of the factors based on 5-points Likert scale of agreeability on the strength of relationship within these factors.

3. Methodology and Data Collection

The data collected for this study was through questionnaire survey. The questionnaire was designed based on factors of knowledge management and innovation learning. Respondents were required to gauge the influence of these factors toward university performance. Respondents of this survey are academic staffs from three public universities in UAE which are higher colleges of technology; United Arab Emirates University and Zayed University.

The total number of respondents is 330 academic staffs of the UAE higher institution of learning. The respondents' background informationis outlined as 79% are males and 21% are females. In terms of marital status, 91% are married, and 9% are single. The ages of respondents between 20 and 30 years old is 16.4%, age between 31 and 40 is 31%, age between 41 and 50 is 29%, age between 51 and 60 is 16.2%, and age over 60 years is 7.6%. In terms of education, participants having high school certificate is 1%, participant with bachelor's degree is 35.2%, participants with master's degree are 40%, and participants with Ph.D. is 24.8%. Taking into account the experience provided in the selected respondents showed that 27.6% have experience from (1-5 years), 29.2% have experience from 6-10 years, 11 to 15 years is 23.4%, and finally over 15 years of experience is 19.8%.

The data collected from the survey was used to develop the mediation model in SmartPLS software. The developed mediation model was assessed at measurement level until it achieved the goodness-of-fit criteria values and then is examined at structural level until it achieves the fitness criteria values. Finally, the model was determined according to the hypothesis as stipulated during the formulation of the hypothetical or conceptual model.

4. Results of Modelling

The data collected through questionnaire survey was used to develop the mediation model in SmartPLS software. The model has inner and outer parts and the evaluation on both parts are basedon PLS-SEM evaluation criteria (Hair et al., 2014).

4.1 Measurement Evaluation

For assessment of the measurement component of the model, it involves two criteria which are convergent validity and discriminant validity.

4.1.1 Convergent Validity

Convergent validity confirms that the scale is correlated with other known measures of the concept. Average Variance Extracted (AVE) should be 0.5 or greater to suggest adequate convergent validity (Hair et al., 2010). According to Kline (2011), a set of variables presumed to measure the same construct shows convergent validity if their inter-correlations are at least moderate in magnitude. According to Sekaran (2006), convergent validity is established when the scores obtained with two different instruments measuring the same concept are highly correlated. The results of convergent validity of the model is as in table 2.

Table 2 - Results of convergent validity

Exogenous Constructs	Items	Loadings	C.R.	AVE	C. Alpha
Knowledge Acquisition	KA1	0.788	0.937	0.679	0.921
	KA2	0.813			
	KA3	0.808			
	KA4	0.707			
	KA5	0.73			
	KA6	0.726			

	KA7	0.716			
Knowledge storage	SK1	0.832	0.931	0.660	0.914
	SK2	0.781			
	SK3	0.813			
	SK4	0.843			
	SK5	0.773			
	SK6	0.821			
	SK7	0.819			
Knowledge Sharing	KSH1	0.852	0.919	0.655	0.895
	KSH2	0.868			
	KSH3	0.779			
	KSH4	0.819			
	KSH5	0.794			
	KSH6	0.739			
Knowledge Application	KAP1	0.831	0.948	0.724	0.937
	KAP2	0.844			
	KAP3	0.822			
	KAP4	0.849			
	KAP5	0.87			
	KAP6	0.881			
	KAP7	0.861			
Innovation Learning	INL1	0.788	0.903	0.573	0.876
	INL2	0.813			
	INL3	0.808			
	INL4	0.707			
	INL5	0.73			
	INL6	0.726			
	INL7	0.716			
Performance	PER1	0.811	0.956	0.664	0.949
	PER2	0.787			
	PER3	0.822			
	PER4	0.762			
	PER5	0.797			
	PER6	0.822			
	PER7	0.86			
	PER8	0.835			
	PER9	0.845			
	PER10	0.824			
	PER11	0.794			

The convergent validity result is shown in table 2 above. All of the items' factor loadings are greater than 0.6, which is the allowed value. Also, AVE values of all constructs are higher than the suggested values of 0.5. Furthermore, all Cronbach's Alpha values are greater than 0.7, which is the ideal value. As a result, all of the measurement models met the convergent validity requirements.

4.1.2 Discriminant Validity

Fornell and Larker criterion, as well as the Cross-loading criterion, have traditionally been used to evaluate discriminant validity. The square root of each measurement model's AVE must be greater than the model's correlation with any other model in the structural model, according to Fornell& Larcker's (1981) criterion for showing discriminant validity. As a result, the square root of each outer model's AVE should be greater than the correlation with any other construct in the current study's Fornell and Larker's test (Hair et al., 2014). Table 3 depicts Fornell and Larker's discriminant validity test.

Table 3 - Discriminant validity results based on Fornell–Larcker criterion

	INN	KA	KAP	KS	KS	Performance
Innovation Learning	**0.757**					
Knowledge Acquisition	0.624	**0.824**				
Knowledge Application	0.620	0.723	**0.851**			
Knowledge Sharing	0.669	0.558	0.721	**0.810**		

Knowledge Storage	0.610	0.716	0.675	0.713	**0.812**	
University Performance	0.648	0.715	0.755	0.637	0.632	**0.815**

The cross-loading test is the second measure of discriminant validity. Chin advocates for the cross-loading criterion (1998). Item loading on their underlying constructs must be higher than cross-loading on other constructs, according to the criterion (Hair et al., 2014; Wong, 2016).

As demonstrated in Table 4, each component in the current study had a stronger cross loading on itself than the other factors, implying discriminant validity.

Table 4 - Cross-loading assessment

	Innovation	Knowledge Acquisition	Knowledge Application	Knowledge Sharing	Knowledge Storage	University Performance
INL1	0.788	0.451	0.464	0.496	0.482	0.498
INL2	0.813	0.526	0.504	0.564	0.573	0.539
INL3	0.808	0.477	0.498	0.516	0.417	0.532
INL4	0.707	0.432	0.45	0.488	0.38	0.434
INL5	0.73	0.335	0.343	0.432	0.352	0.402
INL6	0.726	0.332	0.407	0.488	0.373	0.35
INL7	0.716	0.655	0.556	0.534	0.577	0.602
KA1	0.488	0.812	0.548	0.431	0.599	0.599
KA2	0.51	0.85	0.626	0.453	0.608	0.612
KA3	0.506	0.836	0.624	0.437	0.654	0.627
KA4	0.386	0.762	0.541	0.322	0.531	0.54
KA5	0.518	0.863	0.606	0.472	0.603	0.582
KA6	0.569	0.843	0.582	0.503	0.574	0.581
KA7	0.602	0.799	0.636	0.577	0.558	0.58
KAP1	0.517	0.609	0.831	0.63	0.577	0.731
KAP2	0.479	0.532	0.844	0.596	0.5	0.675
KAP3	0.522	0.56	0.822	0.583	0.545	0.665
KAP4	0.516	0.613	0.849	0.612	0.558	0.697
KAP5	0.547	0.645	0.87	0.644	0.639	0.755
KAP6	0.594	0.713	0.881	0.615	0.611	0.534
KAP7	0.505	0.618	0.861	0.617	0.58	0.519
KSH1	0.632	0.58	0.705	0.852	0.691	0.614
KSH2	0.59	0.522	0.668	0.868	0.611	0.6
KSH3	0.452	0.332	0.502	0.779	0.574	0.444
KSH4	0.602	0.454	0.56	0.819	0.57	0.494
KSH5	0.47	0.302	0.495	0.794	0.472	0.419
KSH6	0.463	0.463	0.526	0.739	0.512	0.481
SK1	0.509	0.611	0.571	0.589	0.832	0.539
SK2	0.436	0.526	0.505	0.518	0.781	0.482
SK3	0.52	0.598	0.532	0.579	0.813	0.511
SK4	0.547	0.621	0.586	0.58	0.843	0.558
SK5	0.424	0.548	0.542	0.589	0.773	0.452
SK6	0.516	0.575	0.558	0.622	0.821	0.509
SK7	0.501	0.586	0.542	0.576	0.819	0.534
UP1	0.487	0.568	0.662	0.454	0.509	0.811
UP2	0.52	0.544	0.693	0.55	0.527	0.787
UP3	0.528	0.552	0.752	0.544	0.508	0.822
UP4	0.507	0.527	0.685	0.489	0.555	0.762
UP5	0.556	0.654	0.756	0.559	0.55	0.797
UP6	0.548	0.656	0.715	0.49	0.566	0.822
UP7	0.552	0.699	0.75	0.519	0.584	0.86
UP8	0.524	0.57	0.677	0.519	0.45	0.835
UP9	0.526	0.574	0.676	0.543	0.517	0.845
UP10	0.537	0.541	0.663	0.508	0.44	0.824
UP11	0.517	0.489	0.613	0.527	0.437	0.794

According to Fornell and Larcker's test, the square root of each measurement model's AVE is greater than the model's correlation with all other constructs in the structural model. The findings of discriminant analysis with the cross-loading criterion are also shown in Table 4. Bold values signify the items' loadings on their structures. Values with a yellow highlight indicate higher-order structures. As the data reveal, all things place a greater burden on their underlying constructions than their cross-loadings with other constructs. As a result, using this criterion, the measurement models achieve discriminant validity.

4.2 Structural Evaluation

The structural model establishes the causal relationships between measurement models (Hair et al., 2014). The interrelationships detailed here are meant to address research questions and test theories. The main goal of structural model evaluation is to assess the model's quality and predictability of endogenous constructs. The path coefficients and their significance, the endogenous construct's coefficients of determination (R2), the exogenous measurement model's effect sizes using Cohen's f2, the model's predictive relevance using cross-validated redundancy (Q2), and the model's global goodness of fit (GoF) are all assessed using the bootstrapping procedure (Hair et al., 2011; Hair et al., 2014; Wong, 2016). A structural model is evaluated using PLS bootstrapping in Figure 2.

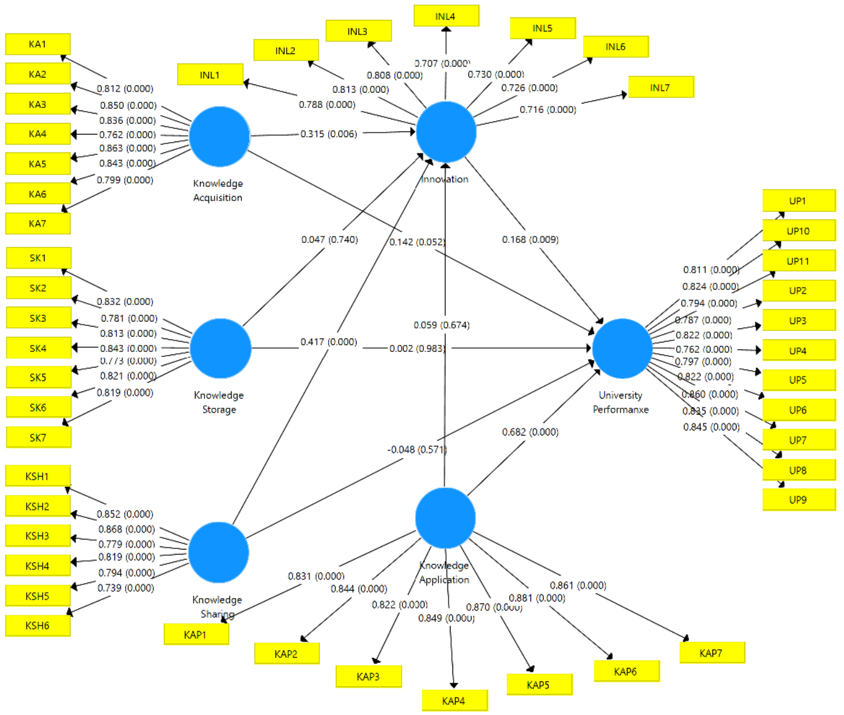

Fig. 2 - Final mediation model

4.2.1 Path Coefficients Evaluation

The strength of linkages between the constructs in the structural model is evaluated using path coefficients. The coefficients values around 1 indicating a strong positive relationship (Hair et al., 2014). The path coefficients are shown in Table 5.

Table 5 - Path coefficients

Path	Path coefficient
Knowledge Acquisition -> University Performance	0.142
Knowledge Storage -> University Performance	0.002
Knowledge Sharing -> University Performance	-0.048
Knowledge Application -> University Performance	0.682
Knowledge Acquisition -> Innovation	0.315
Knowledge Storage -> Innovation	0.047
Knowledge Sharing -> Innovation	0.417
Knowledge Application -> Innovation	0.059
Innovation Learning -> University Performance	0.168
Knowledge Acquisition -> Innovation Learning -> University Performance	0.053
Knowledge Storage -> Innovation Learning -> University Performance	0.008

Knowledge Sharing -> Innovation Learning -> University Performance	0.07
Knowledge Application -> Innovation Learning -> University Performance	0.01

According to table 5, the path values are absolute in nature and the positive or negative is the direction of the path.

4.2.2 Coefficient of Determination (R2) Assessment

Coefficient of determination, also known as R2, reflects the total contribution of the exogenous constructs in explaining or predicting the variance of the endogenous construct in the structural model. The more variance is explained or predicted, the higher the model's quality (Hair et al., 2011; Hair et al., 2014; Wong, 2016). Table 6 shows the R2 for the final model.

Table 6 - R2 evaluation

	R Square	R Square Adjusted
Innovation	0.541	0.532
University Performance	0.765	0.759

Table 6 shows the coefficients of determination (R2) for the study structural model. Innovation learning has an R2 value of 0.532 and university performance has an R2 value of 0.759. This implies that the number is higher than average, implying that the models are highly accurate in their predictions (Hair et al., 2014).

4.2.3 Effect Size (F2) Evaluation

Effect size (f2) is used to calculate the individual contribution of each external component to the R2 (Hair et al., 2011). The relative influence of distinct exogenous constructions on endogenous constructs is represented by Chin's (1998) impact size, which is calculated by estimating changes in the R-squared (s). Cohen's f2 is used to determine the effect size of each component in the structural model. The formula works by removing a specific construct from the model and analysing the outcomes (Hair et al., 2014b).

Effect Sizes: $f^2 = \frac{R^2\,incl - R^2\,excl}{1 - R^2\,incl}$

Where:

f^2 = effect sizes

R^2incl = R^2 inclusive (R^2 with a particular construct included in the model)

R^2excl = R^2 excluded (R^2 with a particular construct excluded from the model)

1= Constant

Table 7 - Effect sizes (F2)

	Innovation Learning	Effect size	University Performance	Effect size
Innovation Learning			0.055	Large
Knowledge Acquisition	0.081	Large	0.030	Small
Knowledge Application	0.030	Small	0.650	Large
Knowledge Sharing	0.143	Small	0.041	Small
Knowledge Storage	0.033	Small	0.032	Small

A small effect size is defined as f2 = 0.02, a medium effect size is defined as f2 = 0.15, and a high effect size is defined as f2 = 0.35, according to Cohen (1988). As stated in table 7, the effect sizes of various research constructs were examined using the criteria listed above.

4.2.4 Predictive Relevance (Q2) Assessment

Cross-validated redundancy is used to determine the predictive value of the structural model. The stone-predictive Geisser's relevance (Q2) was used to examine the data points of all indicators in the outer model of endogenous constructs to see if they could be effectively anticipated (Wong, 2016). This method employs the sample re-use methodology, which entails omitting a section of the data matrix, calculating model parameters, then forecasting the omitted portion using the estimated model parameters (Hair et al., 2011; Hair et al., 2014). In order to have effective predictive relevance, this quality evaluation criterion demands that the cross-validated redundancy (Q2) value be a positive integer greater than 0. (Chin, 1998).

On the basis of the aforementioned submission, the study's final models are evaluated using the blindfolding approach and Smart-PLS software to calculate cross-validated redundancy (Q2) (Ringle, Wende & Becker, 2015). The blindfolding strategy yielded the following results (Table 8).

Table 8 - Predictive relevance

	SSO	SSE	Q^2 (=1-SSE/SSO)
University performance	2211	1111.518	0.497
Innovation	1407	998.044	0.291

Table 8 shows the structural model's cross-validated redundancy. The endogenous constructions' Q2 values are greater than 0. This indicated that the study model was really useful in terms of forecasting (Chin, 1998).

4.2.5 Goodness-of-Fit (GoF) Assessment

PLS-SEM, unlike covariance-based structural equation modelling, lacks a widely accepted global goodness of fit metric (Vinzi et al., 2010). Tenenhaus et al. (2004) presented the "GoF" index as a solution to this problem, which is a global goodness of fit criterion. The geometric mean of the average communality (AVE) index and the average coefficient of determination make up the index (R2). It can be calculated using the following formula:

$$GoF = \sqrt{\overline{AVE2}\ X\ \overline{R2}}$$

The GoF index seeks to explain the performance of the PLS model at both the measurement and structural levels, with a focus on the model's overall prediction performance (Memon & Rahman, 2013). The R2 in the formula represents the structural model, whereas the AVE2 addresses the quality of the index's measurement models. The GoF index of 0.1, 0.25, or 0.36, respectively, implies small, medium, or large (Akter et al., 2011). The model's GoF index is listed below.

$$GoF = \sqrt{0.434\ x\ 0.759}$$

$$GoF = 0.573$$

The formula for computing the goodness of fit index is shown above. The model had a GoF of 0.573. The GoF of the research models is considered high, according to Akter et al. (2011), indicating that the research model is of good quality.

4.3 Hypothesis Testing

The hypothesis testing for this model is divided into three parts where the first part is the direct effect between the independent variables with dependent variable, second part is the direct effect between the independent variables with the mediator variable and finally, the mediation effect of the mediator on the relationship between independent variables with dependent variable.

4.3.1 Direct Effect of Independent to Dependent Variables

Table 9 below shows the P-Values of the direct effect of the independent variables, which are knowledge acquisition, knowledge storage, knowledge sharing and knowledge application. Table 9 shows the hypothesis testing of direct effect through the t-values and p-values.

Table 9 - Results of direct effect of independent to dependent variables

Path	T Statistics	*P Values*	*Findings*
Knowledge Acquisition -> University Performance	1.985	0.048	Supported
Knowledge Storage -> University Performance	0.022	0.983	Not Supported
Knowledge Sharing -> University Performance	0.604	0.546	Not Supported
Knowledge Application -> University Performance	6.655	0.000	Supported

Based on the findings of the above hypotheses, knowledge acquisition and knowledge application have a substantial and direct effect on university performance, while knowledge storage and knowledge sharing do not have a substantial direct effect on university performance.

4.3.2 Direct Effect of Independent to Mediator Variables

Table 10 below shows the P-Values of the direct effect related to the factor innovation. That is, it tested the direct effect of knowledge acquisition, knowledge storage, knowledge sharing, knowledge application on Innovation. It also shows the direct effect of innovation on university performance.

Table 10 - Results of direct effect of independent to mediator variables

Path	T Statistics	*P Values*	*Findings*
Knowledge Acquisition -> Innovation	2.838	0.005	Supported
Knowledge Storage -> Innovation	0.34	0.734	Not supported
Knowledge Sharing -> Innovation	5.132	0.000	Supported
Knowledge Application -> Innovation	0.434	0.665	Not supported
Innovation Learning -> University Performance	2.595	0.010	Supported

Based on the above findings related to the direct effect with the factor innovation learning, it is clear that knowledge acquisition and knowledge sharing have a substantial direct effect on innovation learning, while knowledge storage and knowledge application do not have a substantial direct effect on innovation learning. Moreover, the factor innovation learning has a substantial direct effect on university performance.

4.3.3 Mediating Effect of Innovation Learning on The Direct Relationships

The results of mediation effect of innovation learning variable on the relation between the independent variables (knowledge acquisition, knowledge storage, knowledge sharing, and knowledge application) and the dependent variable (university performance) are as shown in Table 11 below.

Table 11 - Mediation effect of the mediator

Path	T Statistics	P Values	Remark
Knowledge Acquisition -> Innovation Learning -> University Performance	2.205	0.028	Supported
Knowledge Storage -> Innovation Learning -> University Performance	0.333	0.739	Not supported
Knowledge Sharing -> Innovation Learning -> University Performance	2.166	0.031	Supported
Knowledge Application -> Innovation Learning -> University Performance	0.413	0.680	Not supported

According to the above results, it clear that innovation learning has a significant mediating effect between two independent variables (knowledge acquisition and knowledge sharing) and the dependent variable university performance, while it has no significant mediating effect between the other two independent variables (knowledge storage and knowledge application) and the dependent variable university performance.

5. Conclusion

This paper presented research on developing a mediation model on the relationship between KM dimensions and university performance where innovation learning acts as the mediator to the relationship. Based on the assessment/evaluation on the model, it was found that two KM dimensions have a direct significant effect on universities' performance, which are knowledge acquisition and knowledge application. The mediation model comprises of direct effect relationship and mediation effect relationship. For direct effect relationship, it was found that two KM dimensions have a direct significant effect on universities' performance, which are knowledge acquisition and knowledge application. And also, it indicates that there is a significant direct effect for innovation learning on university performance. For mediation effect, it was found that innovation learning on the relationship between KM dimensions (knowledge acquisition, knowledge storage, knowledge sharing, and knowledge application) and universities' performance. The results from this modelling work, indicated that knowledge acquisition and knowledge sharing have a significant indirect effect on universities' performance with partial mediation for knowledge acquisition and full mediation for knowledge sharing.

These findings are concurrent with the theory gathered from previous literatures and contributes body of knowledge to the existing theory of knowledge management explored in the education industry. The findings of this research could benefit academic and decision makers in terms of enhancing organization performance through KM.

Also, innovation learning can be considered as a stimulant to KM in further enhancing the university organization performance.

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