Penerbit UTHM

INTERNATIONAL JOURNAL OF SUSTAINABLE CONSTRUCTION ENGINEERING AND TECHNOLOGY
ISSN: 2180-3242 e-ISSN: 2600-7959

IJSCET

Vol. 15 No. 1 (2024) 88-99
https://publisher.uthm.edu.my/ojs/index.php/ijscet

Effect of Innovation on The Relationship of Knowledge Management Process and Digital Service Performance in UAE Judicial System Model

Hamad Al Katheeri[1], Norliah Kudus[1*]

[1] *Institute of Technology Management and Entrepreneurship, Universiti Teknikal Malaysia Melaka, MALAYSIA*

*Corresponding Author: norliah@utem.edu.my
DOI: https://doi.org/10.30880/ijscet.2024.15.01.007

Article Info

Received: 05 February 2024
Accepted: 05 February 2024
Available online: 26 February 2024

Keywords

Knowledge Management Process, digital service performance, innovation

Abstract

In the UAE's ongoing digital transformation, particularly in the service sector like the Judicial Department, there's a significant gap in understanding the basics of digital innovation, especially in developing countries. Recognizing digital innovation as crucial for government organizations to strengthen their competitive edge by speeding up citizen service, the insufficient exploration of the relationship between knowledge management, digital innovation, and service performance emphasizes the need to bridge this gap for greater efficiency and effectiveness. Hence, this paper reveals a study to establish a mediation model where innovation acts as mediator to the relationship knowledge management processes and digital service performance of the judicial system in UAE. To develop the model, the study adopted quantitative approach where data was collected through questionnaire survey amongst the department's employees. The questionnaire was randomly distributed to the selected 332 employees of the department. The collected data was used to develop and assessed the model in SmartPLS software. It was found that the model has achieved all fitness evaluation criteria with GoF value of 0.766 which indicates the model attain large predictive capability. Hypothesis testing found that for direct relationship between knowledge management processes and digital service performance, the relationship is significant having path strength of 0.504. For indirect relationship between knowledge management processes; innovation and digital service performance, it was found that the relationship is significant having a strength of 0.270. Finally, it was found that the innovation is partially mediates the relationship between management construct and digital service performance. The developed model can be applicable in enhancing innovation to improve the relationship of knowledge management process and digital service performance in UAE Judicial System.

1. Introduction

In the ever-evolving global landscape, technological advancements and knowledge-centric approaches are reshaping the competitive dynamics across countries and industries (Duke, Igwe, Tapang, and Usang, 2022). Faced with the imperative of adaptation and continuous improvement, companies are navigating the challenges of today's enduring global market economy. The response to intense competition and dynamic market demands propels organizations to explore novel strategies and business models, aiming for superior products and services by incorporating new knowledge and technology (Donbesuur, Zahoor, and Adomako, 2021). In this pursuit, organizations actively embrace proven strategies like knowledge management and innovation, recognized for their efficacy in achieving high-performance levels (Jiménez et al., 2017).

In the contemporary era, organizations grapple with uncertainty, complexity, competition, and rapid changes in the business landscape (Tang, Park, Agarwal, and Liu, 2020). Drawing from the knowledge-based view (KBV) of the firm (Khosravani, Nasiri, and Reinicke, 2022), resources tied to knowledge are acknowledged as crucial strategic assets. These resources significantly contribute to the enhancement of the digital service performance of the UAE's judicial system, maintaining a competitive edge in a dynamic and challenging environment (Hurtado-Palomino, De la Gala-Velásquez, and Ccorisapra-Quintana, 2022). The KBV emphasizes that an organization's ability to create value depends on how well it generates, shares, and applies knowledge (Hurtado-Palomino et al., 2022). Particularly, the success of knowledge-intensive business services relies on effective organizational knowledge management (Obeidat et al., 2016).

While knowledge management is equally vital for public sector organizations as it is for their private sector counterparts (Willem and Buelens, 2017), the majority of knowledge management studies have predominantly focused on the private sector (Oluikpe, 2012; Ringel-Bickelmaier and Ringel, 2015). This dearth of scholarly investigation into knowledge management in the public sector, especially concerning service performance issues, raises concerns. Public-sector organizations often lag behind their private-sector counterparts in various aspects of knowledge management (Park, 2017).

A national transition toward a knowledge-based economy necessitates implementing knowledge management programs across federal, state, and semi-government organizations and entities (APO, 2013). However, the scope, power, and roles of each organization or entity differ. In the case of the United Arab Emirates (UAE), governmental operations are distributed between the federal and local governments of each emirate, defined by the UAE's constitution. Despite variations in aims, scope, and responsibilities, government entities at each level play a key role in improving the UAE's economic and social development.

Several needs arise. Firstly, the UAE must assess variations among public sector entities in adopting knowledge management processes. This granular assessment should examine specific functions such as knowledge creation, sharing, capture and storage, and application and use. With this understanding, policymakers and practitioners can provide targeted support to organizations lagging in implementation, including financial incentives and training initiatives aligned with prior research (Balasubramanian et al., 2020). Second, it is essential to understand whether the performance benefits derived from knowledge management process implementation differ among public sector firms. This knowledge can help support performance-benefits-wise laggard public ownership categories (Balasubramanian et al., 2020). Finally, to better manage knowledge management programs, it is critical to understand how specific knowledge management processes have translated to specific performance improvements. Any weak links between knowledge management processes and performance could be selectively improved (Balasubramanian et al., 2020).

The UAE's evolution and its vision for the future are masterfully shaped by the government's commitment to the innovation agenda, with a clear goal of becoming one of the most innovative countries globally (Donbesuur et al., 2021). The UAE introduced several best practices to its National Innovation Strategy in 2015, aiming to generate and adopt new ideas, improve domestic services, and embrace innovative approaches (Balasubramanian et al., 2020). Public sector organizations in the UAE are developing their capabilities but are grappling with deploying innovation practices to improve their services, performance, and operations (Government.ae, 2019b). Most organizations have attempted to use diverse approaches when implementing service innovation and service innovation processes (Shujahat et al., 2019).

Judicial Departments in the UAE, being knowledge-driven organizations, play a vital role in the economic growth and development of the country by generating new ideas through learning and knowledge creation (Al-Yateem, Almarzooqi, Dias, Saifan, and Timmins, 2020). Effective knowledge management processes in justice institutions can improve processes and services, such as speed, quality, development, administration, and strategic planning (Ahmad et al., 2015). Furthermore, innovation is integral to the worldwide agenda of the public sector, contributing directly to the modernization of government and the improvement of judicial performance (Siddiqui and Afzal, 2022; Sousa and Guimaraes, 2017). Hence, this study aimed to develop relationship of Knowledge Management Process (KNP) and Digital Service Performance in UAE Judicial System.

2. Formulation of Conceptual Framework

This research selected the UAE for the investigation because it is one innovative country in the Arab region in which different levels of government organizations have supported KMP programs as part of its 2021 vision (DSG, 2014) to transition from an oil-based economy to a knowledge-based economy in the wake of declining oil prices. Due to the UAE's efforts regarding KMP, it has been ranked first in the Arab world and 42nd overall in the knowledge economy index created by the World Bank (DSG, 2014). Therefore, the UAE is a perfect context to compare the KM processes and subsequent performance of public sector organizations at the federal, state, and semi-government levels (Balasubramanian et al., 2020).

Since there is evidence that KM influences performance (Zwain et al., 2017; Qasrawi et al., 2017; Hung et al., 2017; Yusr et al., 2017), innovation (Honarpour et al. (2017) and that there is a direct relationship between KMP, innovation (Honarpour et al. (2017) and performance (Zwain et al., 2012, Hung et al., 2017; Yusr et al., 2017).

Moreover, the established organisation may preserve its leadership by combining its strategic resources with the development of new complementary resources that respond to the challenges of the digital era (Forcadel et al., 2020). On the other hand, knowledge management and innovation are all topics raised in the business world within a digitalized environment. However, little attention has been paid to service performance. To cover this research gap, this research categorized knowledge management as enhancing the judicial system through innovation.

Finally, as suggested by Sousa and Guimaraes (2014), innovation in the judicial system is a field that needs to be explored, given the lack of such studies compared to innovation studies in general public administration. On the other hand, Innovation in the justice system involves modifying administrative practices commonly associated with the image of those institutions, which means giving up some traditional beliefs and practices (Motta, 2010) in favour of innovation. Changes resulting from adopting knowledge and innovation in the justice system can be seen as a way to improve the system's performance. Hence, additional research is needed in this area. This study was conducted to close this gap.

Based on the literature review above, the following conceptual framework is proposed, as shown in Figure 1. These practices were briefly explained in the next section. KM Process and digital service performance from the previous section 2.3. The research model postulates the KM Process as the independent variable, innovation as the mediator, and Service Performance as the dependent variable. This model was adapted from Iqbal et al. (2019) and Wang and Wang (2012).

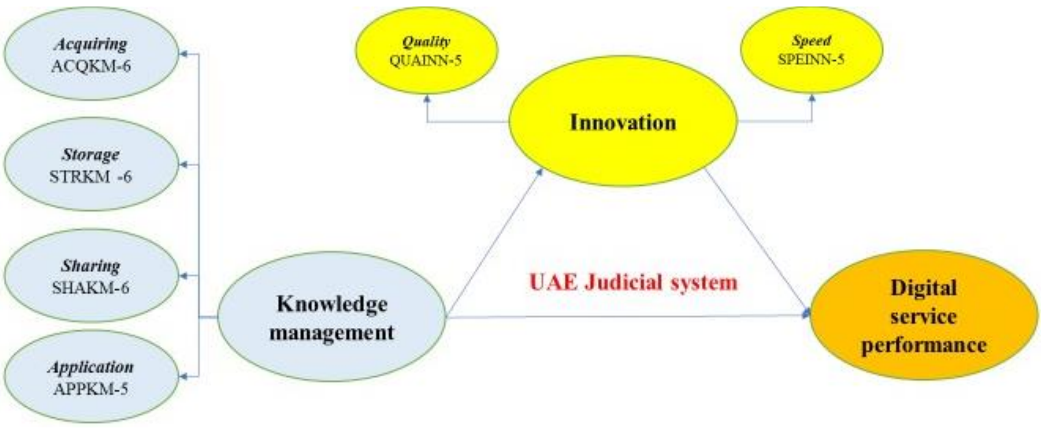


Fig. 1 *Research Framework*

Figure 1 shows the relationship between variables. This model should be regarded as the overall framework for the analysis. Moreover, innovation is the intervening (mediator) variable between KM processes and digital service performance, and the intervening variable equally means the mediating variable established when there are strong relations between the independent and dependent variables via another external variable (mediator) (Sekaran and Bougie, 2010). Sekaran and Bougie (2010) added that the intervening variable always operates as a function of the independent variable. It helps conceptualize and clarify the influence of the independent variable on the dependent variable. In this research framework, innovation is introduced as an intermediate variable. In addition, this research investigates the direct relationships between KM processes and service performance through Innovation.

3. Model Assessment

A structural equation model is developed using PLS-SEM approach in SmartPLS software based on the conceptual model. The developed model is appraised at measurement and structural components of the model in the software until it achieved the fitness criteria. The assessment of measurement component was based on measured convergent validity and discriminant validity values as compared with the criteria values. Composite reliability (CR) and average variance extracted (AVE) values for each latent variable was used to determine convergent validity. Fornell-Larcker criterion and cross loadings values determined discriminant validity. While in the structural component, it assessed path coefficients, coefficient of determination, Goodness of Fit (GoF) and hypothesis testing (Chin, 1998; Henseler et al., 2009; Hair et al., 2016).

3.1 Measurement Component Assessment

Assessment of measurement component involved convergent validity and discriminant validity values as compared with the criteria values.

3.1.1 Convergent Validity

According to (Memon & Rahman, 2013), convergent validity determines the extent to which a measure correlates with an alternative measure of same construct. Thus, convergent validity ensures that an item measures its projected construct. For the present study, the convergent validity was measured by the value of average value extracted (AVE) as suggested by (Waddock and Graves, 1997). An AVE value of 0.50 and above showed the acceptable convergent validity. Since, all the values satisfied the minimum threshold value (0.50) of AVE, thus it showed the acceptable convergent validity for measurement model of the present study. Table 1 contains the values of AVE for the convergent validity of the constructs used in the present study.

Table 1 *Average Variance Extracted (AVE) Values*

Constructs	Code	Average Variance Extracted (AVE)
Knowledge Acquiring	ACQKM	0.671
Knowledge Application	APPKM	0.655
Knowledge Sharing	SHAKM	0.609
Knowledge Storage	STRKM	0.610
Knowledge Management Process	KMP	0.636
Innovation	INN	0.625
Innovation Quality	QUAINN	0.579
Innovation Speed	SPEINN	0.671
Digital Service Performance	SERPE	0.712

Table 1 shows the values of AVE for the convergent validity of the constructs ranges from 0.579 to 0.712 which are above the threshold value of 0.5 which indicates that the measurement component of the model has achieved convergent validity.

3.1.2 Discriminant Validity

According to (Urbach and Ahlemann, 2010), discriminant validity is used to describe how constructs are different from each other. There are two methods to measure discriminant validity of the constructs, (Fornell and Larcker, 1981) criterion and cross-loadings of the construct items. In the first method (Fornell and Larcker, 1981), the value is obtained when the square root of AVE of a construct is greater than its correlation with other constructs. In the second method (Cross-Loading) value indicates that the items loadings are higher of their respective construct and compared to the other constructs. These values indicate the discriminant validity of a measurement model. The values of discriminant validity were obtained through running algorithm function in Smart PLS software. The result showed the values estimated through Fornell- Larcker criterion for measuring discriminant validity which are presented in Table 2.

Table 2*Fornell-Larcker Criterion*

Constructs	INN	KMP	SERPE
INN	0.670		
KMP	0.523	0.653	
SERPE	0.638	0.504	0.844

The second measure to assess discriminant validity is the cross-loadings which are obtained through algorithm generated in Smart PLS software. These values indicated that each measurement item's value is loaded higher for its respective construct as compare to the other constructs. It further showed that each block of values pertaining to a construct contains values higher than the other blocks in similar rows and columns, which clearly separated each latent variable from others. Thus, the cross-loading measure also confirmed the discriminant validity for the measurement model of this study. The values of cross loadings between indicators and constructs are presented in Table 3.

Table 3 *Cross Loadings*

	CONSTRUCTS						
Factors	**ACQKM**	**APPKM**	**QUAINN**	**SERPE**	**SHAKM**	**SPEINN**	**STRKM**
ACQKM1	0.780	0.244	0.285	0.226	0.285	0.250	0.407
ACQKM2	0.873	0.308	0.394	0.239	0.355	0.229	0.459
ACQKM3	0.824	0.203	0.293	0.162	0.272	0.111	0.433
ACQKM4	0.782	0.307	0.298	0.222	0.262	0.299	0.407
ACQKM5	0.790	0.378	0.344	0.303	0.325	0.300	0.491
ACQKM6	0.862	0.257	0.228	0.221	0.284	0.265	0.381
APPKM1	0.283	0.793	0.306	0.359	0.583	0.395	0.558
APPKM2	0.352	0.827	0.375	0.373	0.594	0.353	0.592
APPKM4	0.280	0.879	0.336	0.390	0.709	0.290	0.643
APPKM5	0.197	0.732	0.125	0.258	0.440	0.213	0.369
QUAINN2	0.294	0.254	0.795	0.416	0.212	0.249	0.248
QUAINN3	0.367	0.389	0.786	0.436	0.466	0.402	0.462
QUAINN4	0.294	0.242	0.821	0.411	0.320	0.217	0.337
QUAINN5	0.171	0.203	0.628	0.487	0.216	0.328	0.248
SERPE1	0.251	0.289	0.460	0.844	0.371	0.392	0.368
SERPE2	0.223	0.415	0.455	0.808	0.402	0.384	0.414
SERPE3	0.363	0.338	0.525	0.845	0.423	0.453	0.381
SERPE4	0.234	0.378	0.454	0.874	0.411	0.462	0.376
SERPE5	0.093	0.330	0.469	0.763	0.378	0.457	0.337
SERPE6	0.234	0.345	0.458	0.873	0.417	0.412	0.370
SERPE7	0.252	0.445	0.561	0.891	0.482	0.454	0.447
SHAKM2	0.381	0.664	0.436	0.439	0.863	0.329	0.713
SHAKM3	0.288	0.561	0.280	0.324	0.749	0.231	0.658
SHAKM4	0.260	0.611	0.326	0.424	0.804	0.316	0.704
SHAKM5	0.242	0.556	0.244	0.374	0.737	0.186	0.596
SHAKM6	0.232	0.420	0.294	0.340	0.739	0.124	0.434
SPEINN1	0.279	0.366	0.421	0.454	0.276	0.871	0.345
SPEINN2	0.244	0.329	0.283	0.415	0.306	0.744	0.318
SPEINN3	0.131	0.266	0.218	0.360	0.195	0.770	0.204
SPEINN4	0.288	0.369	0.302	0.436	0.308	0.811	0.340
SPEINN5	0.263	0.274	0.386	0.430	0.209	0.892	0.267
STRKM2	0.741	0.376	0.350	0.238	0.322	0.311	0.584
STRKM3	0.305	0.618	0.306	0.387	0.760	0.245	0.797
STRKM4	0.357	0.550	0.300	0.343	0.635	0.229	0.843
STRKM5	0.276	0.580	0.414	0.452	0.746	0.303	0.802
STRKM6	0.434	0.511	0.333	0.346	0.635	0.327	0.847

To sum up the reliability and validity measures, the tests conducted to analyse data confirmed that the measurement model of the present study is valid and can be further considered to assess the parameters of structural model. Table 4 provides the summary the values of each construct's items factor loadings, CR, and AVE values.

Table 4 *Summary of the assessment model*

Construct	**Factors/ Items**	**Factor Loading**	**CA**	**CR**	**AVE**	**Discriminant Validity**
ACQKM	ACQKM1	0.780	0.902	0.924	0.671	Achieved
	ACQKM2	0.873				
	ACQKM3	0.824				
	ACQKM4	0.782				
	ACQKM5	0.790				
	ACQKM6	0.862				
APPKM	APPKM1	0.793	0.824	0.883	0.655	Achieved
	APPKM2	0.827				

	APPKM4	0.879				
	APPKM5	0.732				
SHAKM	SHAKM2	0.863	0.839	0.886	0.609	Achieved
	SHAKM3	0.749				
	SHAKM4	0.804				
	SHAKM5	0.737				
	SHAKM6	0.739				
STRKM	STRKM2	0.584	0.834	0.885	0.610	Achieved
	STRKM3	0.797				
	STRKM4	0.843				
	STRKM5	0.802				
	STRKM6	0.847				
QUAINN	QUAINN2	0.795	0.840	0.877	0.625	Achieved
	QUAINN3	0.786				
	QUAINN4	0.821				
	QUAINN5	0.628				
SPEINN	SPEINN1	0.871	0.876	0.910	0.671	Achieved
	SPEINN2	0.744				
	SPEINN3	0.770				
	SPEINN4	0.811				
	SPEINN5	0.892				
SERPE	SERPE1	0.844	0.932	0.945	0.712	Achieved
	SERPE2	0.808				
	SERPE3	0.845				
	SERPE4	0.874				
	SERPE5	0.763				
	SERPE6	0.873				
	SERPE7	0.891				

Table 4 presents the summary of the values in the model which has achieved the convergent and discriminant validity criteria of items factor loadings; CA; CR; and AVE.

3.2 Structural Component Assessment

In the structural component, the assessments involved are path coefficients, coefficient of determination, Goodness of Fit (GoF) and hypothesis testing (Chin, 1998; Henseler et al., 2009; Hair et al., 2016),

3.2.1 Path Coefficient

Assessment of the structural model involves an examination of path coefficients, which serve as indicators of the strength and significance of relationships between the variables in question. In the context of SmartPLS, it employs the bootstrapping technique to derive values essential for evaluating the relationships (paths) between independent and dependent variables. This technique is crucial in determining the reliability and significance of the path coefficients within the partial least squares structural equation modelling (PLS-SEM) framework. The procedure begins with the initial estimation of the PLS-SEM model, wherein path coefficients, loadings, and other model parameters are computed using a PLS Algorithm function. Path coefficients are usually between −1 and +1, with coefficients closer to −1 representing strong negative relationships and those closer to +1 indicating strong positive relationships. Figure 2 shows the model after conducting the PLS Algorithm function of the software.

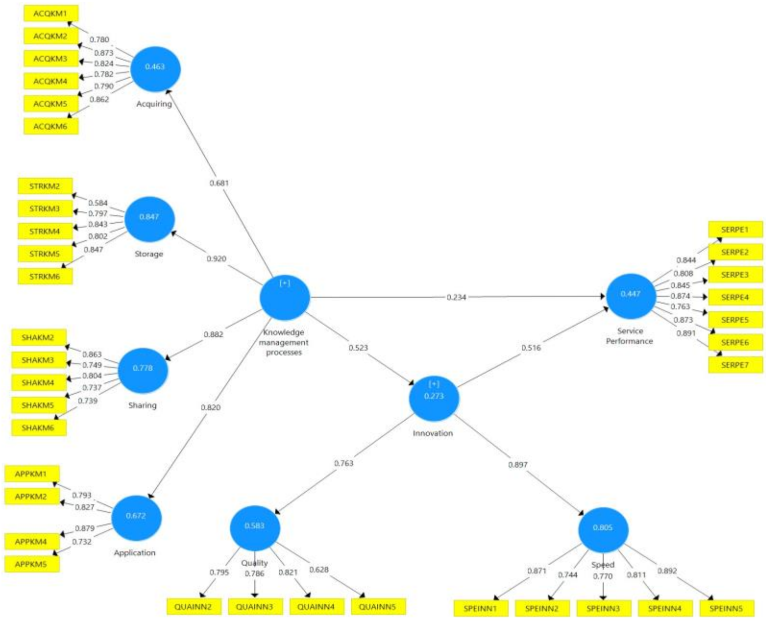


Fig. 2 *After PLS Algorithm*

Results from figure 2 regarding the path coefficients are as in Table 5. The table provides a comprehensive overview of the various paths and their corresponding coefficients, allowing for a nuanced understanding of the direct and indirect relationships between the variables in the structural equation model

Table 5 *Path coefficient/strength*

Path	Direct / indirect	Path coefficient
INN -> SERPE	Direct	0.516
KMP -> INN	Direct	0.523
KMP -> SERPE	Direct	0.234
KMP -> INN -> SERPE	Indirect	0.270
KMP -> SERPE	Total Direct	0.504

Table 5 outlines the relationships between variables in a structural equation model, detailing both direct and indirect effects. The specified paths and their corresponding path coefficients provide insights into the strength and direction of these relationships. Firstly, the "INN -> SERPE" path indicates a direct relationship from variable INN to variable SERPE, with a direct path coefficient of 0.516. This coefficient of 0.516 signifies a positive and moderately strong direct effect from INN to SERPE.

Similarly, the "KMP -> INN" path highlights a direct relationship from variable KMP to variable INN, with a direct path coefficient of 0.523. This coefficient of 0.523 denotes a positive and relatively strong direct effect from KMP to INN. Moreover, the "KMP -> SERPE" path indicates a direct relationship from variable KMP to variable SERPE, with a direct path coefficient of 0.234. This coefficient of 0.234 reflects a positive but comparatively weaker direct effect from KMP to SERPE. The "KMP -> INN -> SERPE" path signifies an indirect relationship from KMP to SERPE through the intermediary variable INN. The indirect path coefficient is 0.270, indicating a positive and moderate indirect effect from KMP to SERPE through the influence of INN.

Finally, the "KMP -> SERPE" (Total Direct) path represents the overall direct effect of KMP on SERPE, considering both direct and indirect paths. The total direct path coefficient is 0.504, encompassing the combined impact of KMP on SERPE through all specified pathways.

3.2.2 Coefficient of Determination

Coefficient of determination (R^2) value is used to explain the amount of variance in dependent variable caused by the independent variables. The higher R^2 values indicate the predictive ability of the structural model. However, the strength of R^2 values depends upon the complexity of research model and type of discipline (F. Hair Jr et al., 2014). If R^2 values of endogenous latent variables are 0.26 it means substantial; 0.13 it means moderate; 0.02 it means weak (Cohen, 1988). on the other hand, R^2 values should be equal to or greater than

0.10 in order for the variance explained of a particular endogenous construct to be deemed adequate (Falk and Miller, 1992). The R2 values for this model are as in Table 6.

Table 6 *Coefficient of Determination (R^2)*

Variable	R^2 Square values	Result
INN	0.273	substantial
SERPE	0.447	substantial

Based on the results from PLS algorithm analysis, as shown in Table 6, 27.3% of the variance in INN was explained by KMP. Furthermore, 44.7% of the variance in SERPE was explained by INN and KMP. Overall, findings illustrate that all R^2 values exceeded the cut-off value of 0.02. The model therefore provides an adequate predictive power for the SERPE.

3.2.3 Model's Goodness-of-Fit (GoF)

The GoF (Goodness of Fit) index aims to clarify the performance of the PLS model, spanning both the measurement and structural models, with a particular focus on the model's overall predictive capability (Memon & Rahman, 2013). Aligned with Akter et al., (2011) classification, GoF is categorized having predictive capability as small, medium, or large when its values are 0.1, 0.25, and 0.36, respectively. The model fitness values resulting from the modelling process are detailed in Table 7.

Table 7 *Model fitness values*

Constructs	Average Variance Extracted (AVE)	R^2 values
ACQKM	0.671	
APPKM	0.655	
INN	**0.625**	0.273
KMP	0.636	
QUAINN	0.579	
SERPE	**0.712**	0.447
SHAKM	0.609	
SPEINN	0.671	
STRKM	0.610	
Average values	0.641	0.360

Table 7 shows the average values of AVE and R^2 of the model. By applying the GoF calculation as follow;

$$\text{Goodness-of-Fit, } GoF = \sqrt{\overline{0.641}\ X\ \overline{0.360}}$$
$$= \sqrt{0.231} = 0.480$$

The outcome of the GoF calculation yields a value of 0.480 which indicates the model attain large predictive capability. Thus, the model's significant predictive capability suggests a robust ability to accurately forecast outcomes or trends based on the provided data and underlying relationships

3.2.4 Hypothesis Testing

In the hypothesis testing of a PLS-SEM model, the bootstrapping process is conducted for assessing the significance of the paths between variables. The bootstrapping process involves drawing multiple samples with replacement from the original dataset. Each bootstrap sample has the same size as the original dataset. For each of these samples, the PLS-SEM model is re-estimated, resulting in a set of parameter estimates for each resampled dataset.

To verify the significance of the paths between variables, it utilizes t-statistics and p-values. As outlined by Hair et al. (2012), if the empirically measured t-value exceeds the critical value, the coefficient is deemed significant at a specified confidence level. In this study, a significance level of p-value of < 0.05 is considered, with a t-value of > 0.95. The application of nonparametric statistical testing, specifically bootstrapping as explained by Hair Jr et al. (2014), further aids in measuring the significance of the estimated path coefficients. Figure 3 show the model that has undergone the bootstrapping process.

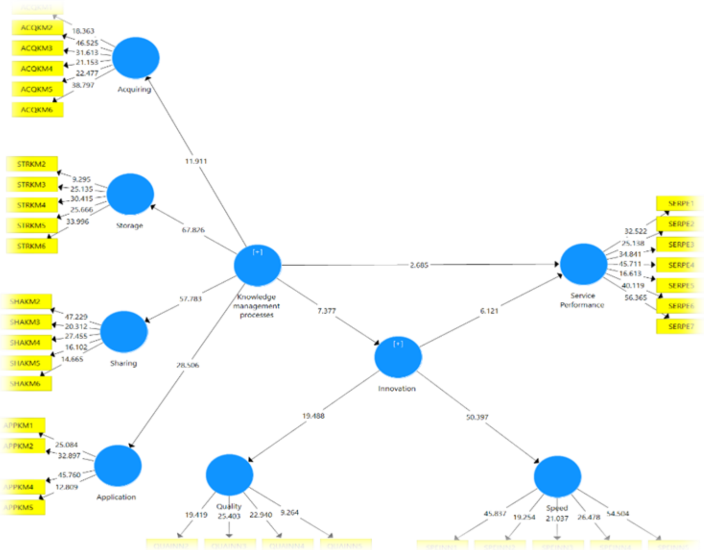


Fig. 3 *After bootstrapping (KMP →INN→SERPE)*

The data derived from bootstrapping represents the outcomes of hypothesis testing, presented in Table 8. This table encompasses various elements, including the identified paths (both direct and indirect), the associated path strength or coefficient, T-statistics, P-values, and concluding remarks regarding the significance level based on the T and P values.

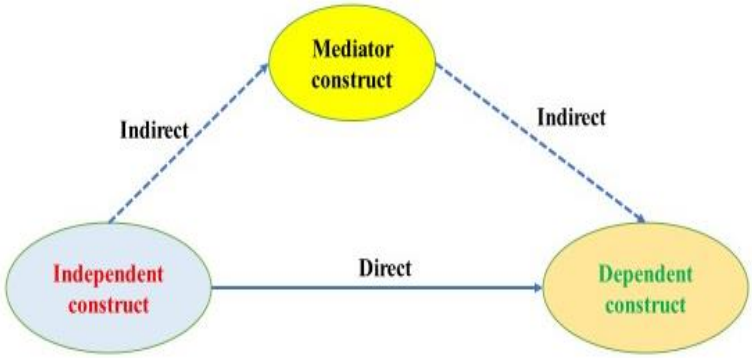
Table 8 *Results of hypothesis testing*

Path	Direct / indirect	Path coefficient	T Statistics	P Values	Level of significant
INN -> SERPE	Direct	0.516	6.121	0.000	Significant
KMP -> INN	Direct	0.523	7.377	0.000	Significant
KMP -> SERPE	Direct	0.234	2.685	0.007	Significant
KMP -> INN -> SERPE	Indirect	0.270	4.454	0.000	Significant
KMP -> SERPE	Total Direct	0.504	7.076	0.000	Significant

Table 8 reveals the significance of all model paths, as evidenced by the T and P values meeting the specified significance criteria.

4. Determination of Mediation Effect

Ghasemy et al. (2020) stated that mediation effects manifest in various forms: full, partial, and no mediations. Full mediation occurs when the direct relationship is not significant, but the indirect relationship is. In contrast, partial mediation occurs when both the direct and indirect relationships are significant. Lastly, no mediation is observed when the direct relationship is significant, but the indirect relationship is not, or when both the direct and indirect relationships are not significant. This mediation effect criteria are summarised in Figure 3.



No	Direct relationship	Indirect relationship	Mediation effect	References
1	Significant	Significant	**Partial**	Ghasemy, M., Teeroovengadum, V., Becker, J.M. and Ringle, C.M., 2020. This fast car can move faster: A review of PLS-SEM application in higher education research. Higher education, 80(6), pp.1121-1152.
2	Significant	Not significant	**No mediation**	
3	No significant	Significant	**Full mediation**	
4	No significant	No significant	**No mediation**	

Fig. 4 *Criteria for mediation effect*

As outlined by Ghasemy et al. (2020), mediation effects manifest in various forms: full, partial, and no mediations. Full mediation occurs when the direct relationship is not significant, but the indirect relationship is. In contrast, partial mediation occurs when both the direct and indirect relationships are significant. Lastly, no mediation is observed when the direct relationship is significant, but the indirect relationship is not, or when both the direct and indirect relationships are not significant. Given that this study specifically aims to understand the mediation effect between the Independent Variable (IV) and Dependent Variable (DV), referring to the results presented in Table 8, the layout of the model focussing on mediation effect is as Figure 5.

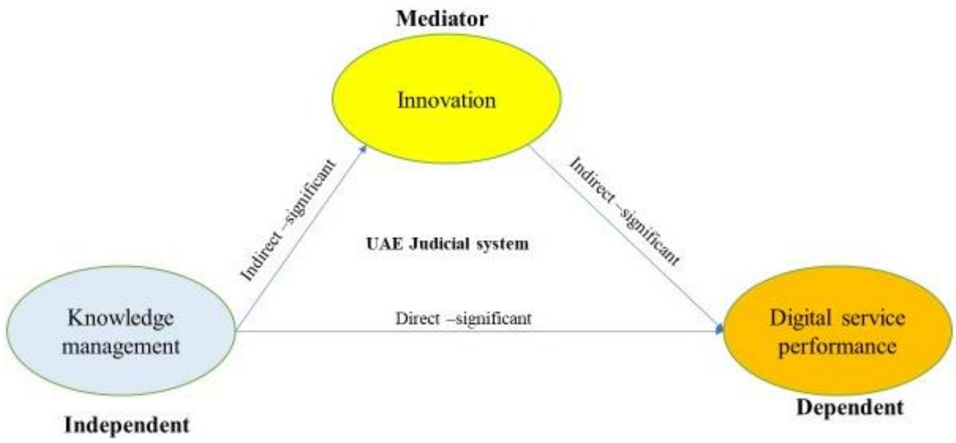


Fig. 5 *Summarised layout of the study mediation effect*

Figure 5 presents the knowledge management construct that is directly significant to digital service performance. Also, knowledge management is indirectly significant to digital service performance via innovation construct. Thus, as outlined by Ghasemy et al. (2020), it can be summarised that the innovation is partially mediates the relationship between management construct and digital service performance.

5. Conclusion

This paper reveals a study to establish a mediation model where innovation acts as mediator to the relationship Knowledge Management processes and Digital Service Performance of the Judicial Department in UAE. To develop the model, the study adopted quantitative approach where data was collected through questionnaire survey amongst the department's employees. The questionnaire was randomly distributed to the selected 332 employees of the department. The collected data was used to develop and assessed the model in SmartPLS software. It was found that the model has achieved all fitness evaluation criteria with GoF value of 0.766 which indicates the model attain large predictive capability. Hypothesis testing found that for direct relationship between Knowledge Management processes and Digital Service Performance, the relationship is significant having path strength of 0.504. For indirect relationship between Knowledge Management processes; Innovation and Digital Service Performance, it was found that the relationship is significant having a strength of 0.270. Finally, it was found that the innovation is partially mediates the relationship between management construct and digital service performance. The developed model can be applicable in enhancing innovation to improve the relationship of knowledge management process and digital service performance in UAE Judicial System.

Acknowledgement

The authors would like to thanks the university for assisting in conducting this study successfully.

References

Ahmad, S. (2015). Green human resource management: Policies and practices. Cogent business & management, 2(1), 1030817.

Akter, S., D'ambra, J., and Ray, P. 2011. An evaluation of PLS based complex models: the roles of power analysis, predictive relevance and GoF index.

Al-Yateem, N., Almarzooqi, A., Dias, J., Saifan, A., and Timmins, 2020. Leadership for professional advancement and evidence-based practice in UAE: Now more than ever. Journal of Nursing Management. https://doi.org/10.1111/jonm.13075.

Balasubramanian, S., Jain, N., Jindal, G., Awasthi, A., & Sarawagi, S. (2020). What's in a Name? Are BERT Named Entity Representations just as Good for any other Name?. arXiv preprint arXiv:2007.06897.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. Modern methods for business research, 295(2), 295-336.

DSG, 2014, “UAE in the context of knowledge management”, Dubai Smart Government e4all, Dubai, Vol. 16 (126).

Donbesuur, F., Zahoor, N., and Adomako, 2021. Postformation alliance capabilities and environmental innovation: The roles of environmental in-learning and relation-specific investments. Business Strategy and the Environment, 30(7), 3330–3343. https://doi.org/10.1002/bse.2805

Duke, J., Igwe, V., Tapang, A., and Usang, 2022. The innovation interface between knowledge management and firm performance. Knowledge Management Research and Practice, 1–13. https://doi.org/10.1080/14778238.2022.2029596.

F. Hair Jr, J., Sarstedt, M., Hopkins, L., and G. Kuppelwieser, 2014. Partial least squares structural equation modeling (PLS-SEM) An emerging tool in business research. European Business Review, 26(2), 106–121.

Forcadell, F. J., Aracil, E., & Úbeda, F. (2020). The impact of corporate sustainability and digitalization on international banks' performance. Global Policy, 11, 18-27.

Fornell, C., Larcker, D. F., and Modeling, 1981. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research (JMR). Feb1981, 18(1), 39-50. 12p. 1 Diagram. https://doi.org/10.2307/3151312.

Ghasemy, M., Teeroovengadum, V., Becker, J. M., & Ringle, C. M. (2020). This fast car can move faster: A review of PLS-SEM application in higher education research. Higher education, 80(6), 1121-1152.

Government, 2019.“The UAE Government”, available at: https://u.ae/en/about-the-uae/the-uaegovernment (accessed August 24, 2019).

Hair Jr, J. F., Hult, G. T. M., Ringle, C., and Sarstedt, 2016. A primer on partial least squares structural equation modeling (PLS-SEM). Sage publications.

Hair, J. F. J., Hult, G. T. M., Ringle, C., and Sarstedt, 2014. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Long Range Planning (46).

Hair, J. F., Sarstedt, M., Pieper, T. M., and Ringle, 2012. “The use of partial least squares structural equation modeling in strategic management research: a review of past practices and recommendations for future applications”, Long range planning, 45(5-6), pp. 320-340.

Henseler, J., Ringle, C. M., and Sinkovics, 2009. The use of partial least squares path modeling in international marketing. In New challenges to international marketing, pp. 277-319. Emerald Group Publishing Limited.

Honarpour, A., Jusoh, A. and Long, 2017, “Knowledge management and total quality management: a reciprocal relationship”, International Journal of Quality and Reliability Management, 34(1), pp. 91-102.

Hung, R. Y., Lien, H., Fang, S. C., and McLean, 2011. “Knowledge as a facilitator for enhancing innovation performance through total quality management”, Total Quality Management and Business Excellence, 21(4), pp.425–438.

Hurtado-Palomino, A., De la Gala-Velásquez, B., and Ccorisapra-Quintana, 2022. The interactive effect of innovation capability and potential absorptive capacity on innovation performance. Journal of Innovation and Knowledge, 7(4), 100259. https://doi.org/10.1016/j.jik.2022.100259.

Iqbal, Sajid, Muhammad U. Ghani Khan, Tanzila Saba, Zahid Mehmood, Nadeem Javaid, Amjad Rehman, and Rashid Abbasi. "Deep learning model integrating features and novel classifiers fusion for brain tumor segmentation." Microscopy research and technique 82, no. 8 (2019): 1302-1315.

Jiménez, A., Boehe, D. M., Taras, V., & Caprar, D. V. (2017). Working across boundaries: Current and future perspectives on global virtual teams. Journal of International Management, 23(4), 341-349.

Khosravani, M. R., Nasiri, S., and Reinicke, 2022. Intelligent knowledge-based system to improve injection molding process. Journal of Industrial Information Integration, 25, 100275. https://doi.org/10.1016/j.jii.2021.100275.

Memon, A. H., & Rahman, I. A. (2013). Analysis of cost overrun factors for small scale construction projects in Malaysia using PLS-SEM method. Modern applied science, 7(8), 78.

Motta, P. R. M. (2010). Revendo estrategicamente as organizações do Poder Judiciário: uma perspectiva gerencial. Cadernos FGV Projetos, 5(12), 24-31.

Obeidat, B.Y., Al-Suradi, M.M., Masa'deh, R.E. and Tarhini, 2016, "The impact of knowledge management on innovation: an empirical study on Jordanian consultancy firms", Management Research Review, 39(10), pp. 1214-1238.

Oluikpe, 2012, "Developing a corporate knowledge management strategy", Journal of Knowledge Management, 16(6), pp. 862-878.

Qasrawi, B. T., Almahamid, S. M. and Qasrawi, 2017. "The impact of TQM practices and KM processes on organisational performance: An empirical investigation", International Journal of Quality and Reliability Management, 34(7), pp. 1034–1055.

Shujahat, M., Sousab, M. J., Hussain, S., Nawaz, F., Wang, M., and Umer, 2019. Translating the impact of knowledge management processes into knowledge-based innovation: The neglected and mediating role of knowledge-worker productivity. Journal of Business Research, 94, 442–450.

Siddiqui, S. A., and Afzal, 2022. Sectoral diversification of UAE toward a knowledge-based economy. Review of Economics and Political Science. https://doi.org/10.1108/reps-07-2021-0075.

Sousa, M. D M., & Guimaraes, T. A. (2014). Innovation and performance in judicial management: uncovering conceptual and methodological gaps (Inovação e desempenho na administração judicial: desvendando lacunas conceituais e metodológicas). Review of Administration and Innovation – RAI, 11, 321–344. doi: 10.5773/rai.v11i2.1373.

Tang, G. X., Park, K., Agarwal, A., and Liu, 2020. Impact of innovation culture, organization size and technological capability on the performance of SMEs: The case of China. Sustainability (Switzerland), 12(4). https://doi.org/10.3390/su12041355.

Urbach, N., and Ahlemann, 2010. "Structural equation modeling in information systems research using partial least squares", Journal of Information technology theory and application, 11(2), pp. 5-40.

Waddock, S. A., and Graves, 1997. The corporate social performance-financial performance link. Strategic Management Journal. https://doi.org/10.1002/(SICI)1097-0266(199704)18:4<303::AID-SMJ869>3.0.CO;2-G.

Wang, Z. and Wang, 2012. "Knowledge sharing, innovation and firm performance", Expert Systems with Applications, 39(10), pp. 8899-8908.

Willem, A. and Buelens, 2017 "Knowledge sharing in public sector organizations: the effect of organizational characteristics on interdepartmental knowledge sharing", Journal of Public, 7(2) pp.14-20.

Yusr, M. M., Mokhtar, S. S. M., Othman, A. R., and Sulaiman, 2017. Does interaction between TQM practices and knowledge management processes enhance the innovation performance? International Journal of Quality and Reliability Management, 34(7), 955–974.

Zwain, A. A. A., Lim, K. T., & Othman, S. N. (2017). TQM and academic performance in Iraqi HEIs: associations and mediating effect of KM. The TQM Journal, 29(2), 357-368.

Sekaran, U., and Bougie, R., 2010. Research Methods for Business: A Skill Building

APO, 2013, "Knowledge management for the public sector" Asian productivity organization.

Park, 2017, "The comparison of knowledge management practices between public and private organizations: an exploratory study", doctoral dissertation, The Pennsylvania State University, PA.