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Associating Technology Innovation Domains with Quality Service Performance of Public Health Care Organizations

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Abstract: This paper has presented the modelling of three technology innovation domains namely Organization Innovation Capabilities; Potential Absorptivity Knowledge; and Interaction with Technology affecting the UAE Health Care organisation performance construct. The modelling processes was conducted in SmartPLS software using 398 data gathered through questionnaire survey amongst employees of UAE public health care organization. Results from the modelling analysis found that model fitness criteria, which are Chi-Square value and NFI (Normed Fit Index) have an acceptable fit index. The model also has excellent predictive relevance for independent constructs that have fully account for the variance in dependent construct. however, one of the three paths was found not significant which is the path from OIC to OP. In term of path strength, paths from the construct OP to IWT has coefficient value of 0.3; to OIC has coefficient value of 0.1; and to PAK has coefficient value of 0.4. It is hope that the findings from this study have contributed to the knowledge of the relationship between the technology innovation dimension affecting the UAE public health care organization.

Keywords: Technology innovation, quality service performance of public health care

1. Introduction

Globally, technological innovations are constantly progressing. However, there is a lack of research on healthcare service quality in the Middle East, with only a few studies looking at healthcare service quality in relation to organisational performance in the UAE (Aburayya et al., 2020a). As a result, empirical study in this area is required in the UAE in order to highlight the essential variables of healthcare service quality and their impact on patient satisfaction. Because most of the population prefers to seek medical care outside of the country rather than visiting hospitals within the country, the quality of health services in the UAE requires investigation (Lee & Kim, 2017). In general, Emiratis' income is rising, and so are patients' expectations and awareness of medical services. As a result, hospitals must contribute significantly to the improvement of healthcare quality in order to deal with such shifts (Abu-Rumman et al., 2021). That is, even if healthcare practitioners deliver the finest medical treatments to patients, service quality will decrease if patients are unhappy with the services provided (Lee & Kim, 2017).

According to Aburayya et al. (2020a), another challenge in the UAE's healthcare sector is that healthcare administrators and policymakers see limited access to hospitals by UAE people as a serious concern, particularly in primary healthcare institutions. Because it disrupts patient flow, a huge number of people are dissatisfied with healthcare services. This is because, at most hospitals, patient wait times are determined on a first-come, first-served basis. To

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compete in terms of offering a great patient experience, healthcare organisations must create and implement strategies that allow patients to access services on time (Al-Neyadi et al., 2018). As a result, the UAE's primary healthcare sector expects increased process efficiency and lower patient wait times, both of which are indicators of poor healthcare quality.

Furthermore, as a result of the current global trend towards technology, the UAE government is giving increased attention to these technologies and their usage in the health sector. The UAE government has created Vision 2030, which aims to improve AI application across the country with the objective of achieving 100% automation by 2020 by making the UAE a smart country (UAE 2031, 2018). However, studies on technology elements of service quality in the health industry are still sparse in the UAE. As a result, the current study seeks to analyse the Technology Innovation characteristics that influence the performance of government hospitals in the UAE. The goal is to create a model that can be used to improve organisational culture through improved utilisation of healthcare service technologies, hence supporting the performance of healthcare providers in the UAE.

2. Healthcare Service Quality (OP)

A hospital must offer services that are appropriate for the population it serves in terms of health needs. Researchers concur that improving service quality can lead to higher customer retention, a competitive advantage, and long-term profitability (Giovanis et al., 2018). One method of improving the responsiveness of health services to people's needs is to incorporate patient opinions into quality assessment (Halvorsrud et al., 2016). Donabedian (1980) proposed the structure-process-outcome model in the literature on healthcare, which was created to consider the peculiarities of the healthcare industry. Additionally, many nations have adopted the SERVQUAL (Parasuraman et al., 1988) model to analyze service quality in the healthcare sector (Altuntas et al., 2020; Untachai, 2013). In addition to the SERVQUAL-based models, there are other frameworks derived from focus groups or patient interviews. The study in Korea provided a four-factor structure, including tangibles, staff concerns, physician concerns, and process concerns (Choi et al., 2005). In their 2010 study, Chahal and Kumari focused on an Indian-specific conceptual framework for healthcare quality that was based on a modified version of Brady and Cronin's (2001) hierarchical model.

Thawesaengskulthai et al. (2015) investigated how various patient groups from Asia, Europe, Australia, and North America who received medical care in Thailand perceived and measured hospital service quality. They discovered that the nationality and demographics of the patient population should be taken into account when developing the service quality measurement model, in addition to context-specific factors like size and location. There is no agreement among researchers as to what constitutes high-quality hospital services. They all concur, though, that service quality is multifaceted. The healthcare sector has also changed how services are provided as a result of patient expectations for better service, technological advancements, better internet and digital media access to health information, and a more comprehensive approach to health and wellbeing issues (Akbar et al., 2020). Given the current state of knowledge and technology, hospitals in the traditional medical environment place a strong emphasis on raising the likelihood of favorable healthcare outcomes. Researchers were motivated to learn more about how customers evaluate IT-based services and how their evaluations impact how they perceive the overall quality of the service provider's and their own satisfaction as a result of the growing importance of information technology (IT) (Kokkinou and Cranage, 2015; Xiaofei et al., 2021).

3. Technology Innovation Domain

Technology Innovation Management is the process of controlling, guiding, and managing the creation and execution of fresh corporate strategies and technical advances. This strategy is meant to facilitate the expansion of current businesses. The followings are the factors in technology innovation domain.

3.1 Organization Innovation Capabilities (OIC)

While recognizing the varying levels of innovative capability across different firms, it is essential to focus on multiple factors simultaneously in innovative endeavours, encompassing new products, marketing practices, organizational strategies, administrative systems, and process technologies (Edu et al., 2020; Migdadi, 2020; YuSheng & Ibrahim, 2020). Moreover, the introduction of administrative and technical innovations in a balanced manner tends to be more advantageous than pursuing them in isolation, facilitating businesses in enhancing and sustaining their performance. While the literature on innovation doesn't definitively establish the greater or lesser impact of specific innovation types on corporate performance, it highlights their interconnectedness, emphasizing the need for their coordinated implementation (Mendoza-Silva, 2020). Notably, research suggests that organizational (re)structuring, leading to administrative and structural enhancements, serves as a catalyst for other forms of innovations. For instance, Rahmah et al. (2020) found that administrative innovations triggered technical innovations. Similarly, Brosig (2020) emphasized collaborative organizational redesigns and coordination frameworks as instrumental in propelling technological advancements within organizations. More recently, Cheng and Wang (2022) explored the interrelationships between organizational, marketing, and service innovations.

3.2 Potential Absorbing Knowledge (PAK)

When organizations are confronted with novel challenges or the need to refine existing processes to enhance potential outcomes or bridge the gap between expectations and results through information processing, the concept of organizational learning gains significance (Fan et al., 2021). A growing number of businesses today are actively seeking external knowledge to bolster their competitive edge and drive innovation. The role of a company's ability to absorb knowledge has been underscored as a potential key to successful innovation (Rezaei-Zadeh & Darwish, 2016). The notion of potential absorptivity is closely tied to learning and the assimilation of external knowledge (Oksanych, 2020). The capability to effectively integrate external knowledge into existing organizational knowledge often serves as a strong indicator of an individual's learning capacity. The process through which organizations identify, assimilate, and apply external knowledge or information is referred to as knowledge absorptivity (Sein & Vavra, 2020). According to Cárcel-Carrasco and Gómez-Gómez (2021), industries demand extensive knowledge acquisition and mastery of complex technical and human factors to excel in producing processes or services. Although integrating these competitive advantages into operational strategies is crucial, the absorption, management, and application of knowledge in this context often go unaddressed. The advent of Industry 4.0 underscores the strategic and vital role of knowledge and necessitates a comprehensive examination of organizational processes, internal structures, and knowledge utilization (Zhao et al., 2020). It's essential to consider the internal organizational dynamics when analysing procedures, visualizing knowledge creation and assimilation, and identifying the existing knowledge reservoir.

3.3 Interaction with Technology (IWT)

The advancement of mobile information technology has facilitated businesses to employ diverse self-service technologies, expanding service channels and enhancing customer engagement, thereby revolutionizing the service landscape. Current self-service technology interfaces utilized by organizations encompass kiosks, the internet, interactive voice response, and mobile services (Oliveira et al., 2021). Human-technology interaction denotes the interaction between customers and self-service facilities. In this study, we assess human-technology interaction effectiveness through two subdimensions: technical convenience and technical security along with information quality. The subdimension of technical convenience evaluates the accessibility of self-services through technology, offering customers convenience at any time and location. Technical convenience significantly influences customer loyalty (Wang, 2012). Customer loyalty hinges on the convenience, reliability, and user-friendliness of the technology (Darzentas and Helen, 2019). Sub-dimensions of technical security and information quality pertain to information handling, safety, and technology usage. In technology-based transactions, customers are concerned about information security and accuracy (Herath et al., 2020). Technology providing real-time comprehensive information for self-service tasks enhances perceived service quality for customers. Conversely, perceptions of risk and uncertainty negatively affect customer attitudes toward self-service technologies (Hameed & Arachchilage, 2020).

4. Conceptual Model

The research's conceptual model has been formulated based on the identified research factors, visually representing the interplay and connections among the research variables. This model visually depicts how the researcher operationalized the research variables, illustrating their relationship between the independent and dependent variables. Previous sections have discussed the variables identified within the service quality's technology innovation dimensions, impacting healthcare organizations' performance. The study comprises three independent variables: organization innovation capabilities, Potential Absorbing knowledge, and Interaction with technology, all of which directly influence the dependent variable, healthcare organizations' performance in the UAE. The linkage between the independent and dependent variables represents a direct effect. The Figure 1 illustrates the research's conceptual model.

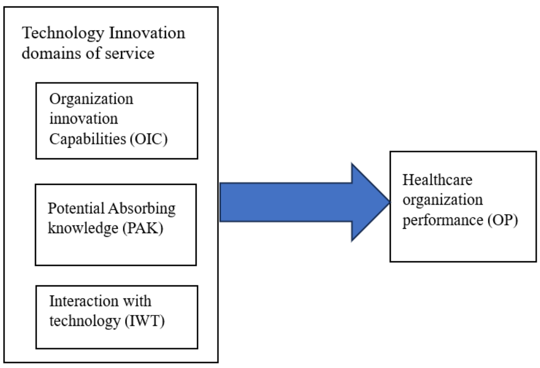

Fig 1 - Conceptual model

Based on the research conceptual model, the following hypotheses are formulated:
(**H1**): The performance of healthcare public organizations in the UAE is positively influenced by organization innovation capabilities (OIC).
(**H2**): The performance of healthcare public organizations in the UAE is positively affected by potential absorbing knowledge (PAK).
(**H3**): The performance of healthcare public organizations in the UAE experiences a positive impact from interaction with technology (IWT).

5. Modelling of PLS-SEM

The technique of Partial Least Squares (PLS) path modelling, known as PLS structural equation modelling (PLS-SEM), was initially developed by Wold (1982) and subsequently refined by Lohmöller (1989). Essentially, the PLS-SEM algorithm consists of a sequence of regressions involving weight vectors, with these vectors aligning with fixed point equations at convergence. The modelling of the conceptual framework in the SmartPLS software comprises three core steps: running the PLS algorithm, conducting Blindfolding, and performing Bootstrapping. Herein, the subsequent sections provide detailed explanations of these three processes.

5.1 PLS Algorithm

Purpose of running the PLS Algorithm is to determine the construct reliability & validity; discriminant validity; path coefficient; and model fitness. After the model was created based on the conceptual model and the data was assigned to the respective constructs, the PLS Algorithm function was run on the model and the result is as in figure 2

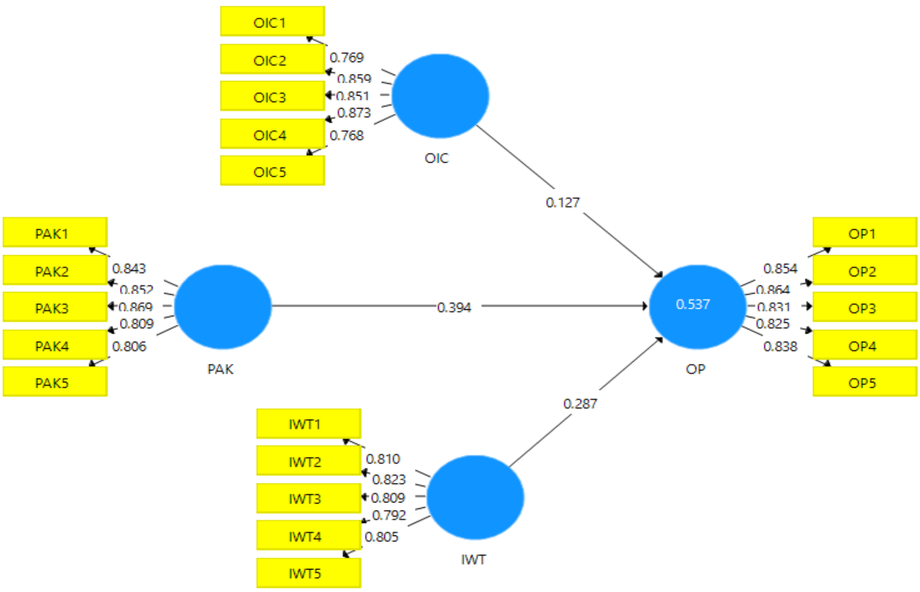

Fig 2 - of PLS Model after conducting

Figure 2 shows the generated model after conducting PLS Algorithm. It requires to check the construct reliability & validity; discriminant validity; path coefficient; and model fitness values that have been generated through the PLS Algorithm function of the software.

5.1.1 Construct Reliability and Validity

Construct reliability refers to the degree of consistency and stability in measuring a specific psychological construct, ensuring that the results are dependable and reproducible over time. On the other hand, construct validity assesses the extent to which a measurement truly captures and represents the intended theoretical concept, providing evidence that the measurement accurately measures the underlying construct it is designed to assess.

Table 1 - Generated results of construct reliability and validity

Construct	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
IWT	0.867	0.871	0.904	0.653

OIC	0.882	0.886	0.914	0.681
OP	0.898	0.898	0.924	0.709
PAK	0.892	0.896	0.921	0.699

Table 1 presents the reliability and validity measures for four different constructs: IWT, OIC, OP, and PAK. Cronbach's Alpha, rho_A, Composite Reliability, and Average Variance Extracted (AVE) are reported for each construct. All constructs demonstrate high levels of internal consistency and reliability, with values ranging from 0.867 to 0.898 for Cronbach's Alpha. Additionally, the Composite Reliability scores, ranging from 0.904 to 0.924, indicate excellent construct reliability. Moreover, the Average Variance Extracted (AVE) values, ranging from 0.653 to 0.709, suggest that the constructs share more variance with their respective indicators than with measurement error, confirming good construct validity (Hair, J.E. et.al. 2017).

5.1.2 Discriminant Validity

In discriminant validity, it requires to check three criteria which are HTMT criterion; Cross Loading; and Fronell-Larcker criterion values that have been generated through the PLS Algorithm function.

5.1.2.1 HTMT Criterion

HTMT criterion measures the average correlations of the indicators across constructs. The acceptable levels of discriminant validity (< 0.90) as suggested by Henseler et al. (2015). It is recommended for identifying distinctiveness of the constructs but should be used taking 0.85 or 0.90 cautiously (Hair, J.E. et.al. 2017).

Table 2 - Generated results of HTMT criterion

Constructs	IWT	OIC	OP	PAK
IWT				
OIC	0.751			
OP	0.733	0.677		
PAK	0.812	0.822	0.769	

Table 2 represents the Heterotrait-Monotrait (HTMT) ratio of correlations for four constructs: IWT, OIC, OP, and PAK. The HTMT is a criterion used to assess discriminant validity in structural equation modelling (SEM) by comparing the correlations between different constructs (heterotrait) to the correlations within the same construct (monotrait). In this table, the values represent the ratios of correlations, and if all the HTMT values are less than 1, it suggests that the constructs have discriminant validity, meaning they are distinct from each other and are measuring unique concepts (Hair, J.E. et.al. 2017). However, without the specific values filled in the table, it is not possible to determine whether the criterion is met in this case.

5.1.2.2 Cross Loadings

According to Cross loadings, a particular item should have higher loadings on its own parent construct in comparison to other constructs in the study. If an item loads well onto another construct in comparison to its own parent construct, then there are issues of discriminant validity

Table 3 - Generated results of cross loading

	Constructs			
Factors	IWT	OIC	OP	PAK
IWT1	0.81	0.587	0.532	0.57
IWT2	0.823	0.521	0.493	0.548
IWT3	0.809	0.511	0.509	0.562
IWT4	0.792	0.534	0.476	0.574
IWT5	0.805	0.497	0.605	0.623
OIC1	0.535	0.769	0.453	0.525
OIC2	0.549	0.859	0.525	0.644

OIC3	0.544	0.851	0.494	0.622
OIC4	0.564	0.873	0.534	0.642
OIC5	0.511	0.768	0.479	0.573
OP1	0.568	0.496	0.854	0.555
OP2	0.556	0.495	0.864	0.562
OP3	0.529	0.528	0.831	0.571
OP4	0.521	0.511	0.825	0.593
OP5	0.57	0.511	0.838	0.63
PAK1	0.538	0.631	0.629	0.843
PAK2	0.596	0.594	0.572	0.852
PAK3	0.619	0.595	0.597	0.869
PAK4	0.631	0.638	0.58	0.809
PAK5	0.613	0.596	0.503	0.806

Table 3 presents the cross-loading values for different factors (IWT, OIC, OP, PAK) and their respective indicators (IWT1 to IWT5, OIC1 to OIC5, OP1 to OP5, PAK1 to PAK5). The values represent the strength of the relationship between each indicator and its corresponding factor. It indicates that each indicator shows the highest cross-loading value on its corresponding factor, which is desirable in PLS as it indicates that each indicator is primarily associated with its intended construct. For example, the indicators IWT1 to IWT5 have their highest loadings on the factor IWT, OIC1 to OIC5 have their highest loadings on the factor OIC, and so on. The cross-loading values are relatively high for most indicators, suggesting that the indicators are well-aligned with their respective constructs. This supports the convergent validity of the model, indicating that the selected indicators effectively represent the underlying latent constructs and contribute to measuring them accurately (Hair, J.E. et.al. 2017).

5.1.2.3 Fronell-Larcker Criterion

The Fronell-Larcker criterion is one of the most popular techniques used to check the discriminant validity of measurements models. According to this criterion, the square root of the average variance extracted by a construct must be greater than the correlation between the construct and any other construct (Hair, J.E. et.al. 2017).

Table 4 - Generated results of Fronell-Larcker criterion

Constructs	IWT	OIC	OP	PAK
IWT	**0.808**			
OIC	0.655	**0.825**		
OP	0.652	0.603	**0.842**	
PAK	0.715	0.731	0.692	**0.836**

The Fornell-Larcker criterion assesses the discriminant validity in a structural equation model for four constructs: IWT, OIC, OP, and PAK. The diagonal values represent the square root of the Average Variance Extracted (AVE) for each construct, while the off-diagonal values show the correlations between the constructs. Based on the table 4, all diagonal values (ranging from 0.808 to 0.842) are higher than the corresponding off-diagonal values, indicating that the constructs meet the Fornell-Larcker criterion for discriminant validity. This suggests that each construct has more variance captured by its own indicators than shared with other constructs, confirming that they are distinct and represent separate concepts in the model.

5.1.3 Path Coefficient

A path coefficient is interpreted: If X changes by one standard deviation Y changes by b standard deviations (with b being the path coefficient). In terms of relevance, 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 (Hair, J.E. et.al. 2017).

Table 5 - Generated results of path coefficient

Constructs	OP
IWT	0.3
OIC	0.1
PAK	0.4

Table 5 represents the path coefficients in a Partial Least Squares (PLS) model for four constructs: IWT, OIC, PAK, and OP. The path coefficients indicate the strength and direction of the relationships between the constructs in the model. From the table, it is evident that there are paths from the construct OP to IWT (path coefficient of 0.3), OIC (path coefficient of 0.1), and PAK (path coefficient of 0.4). This suggests that OP is the dependent variable in the model, and its values are influenced by IWT, OIC, and PAK.

5.2 Model Fitness

The PLS model fitness is evaluated by comparing the fit indices of the Saturated Model and the Estimated Model. The values for SRMR (Standardized Root Mean Square Residual), d_ULS (degree of Unweighted Least Squares), and d_G (degree of Geodesic) are the same for both models, which indicates that the Estimated Model is performing equally well in terms of these fit indices.

Table 6 - Generated results of model fitness

Items	Saturated Model	Estimated Model
SRMR	0.055	0.055
d_ULS	0.627	0.627
d_G	0.339	0.339
Chi-Square	800.747	800.747
NFI	0.856	0.856

Table 6 show that the Chi-Square value of 800.747 is the same for both models as well, but it should be noted that in PLS-SEM, the Chi-Square test is not commonly used for model fit assessment. The NFI (Normed Fit Index) of 0.856 for both models indicate a good fit, with values closer to 1 indicating a better fit. Overall, the Estimated Model seems to have an acceptable fit based on the given fit indices.

5.3 Blindfolding

The objective of predictive relevance lies in evaluating the model's capacity to accurately forecast outcomes and generalize to novel, unseen data. Metrics like Q^2 (Q squared) within Partial Least Squares (PLS) assess the model's predictive ability by gauging its performance in foreseeing dependent variables based on independent predictors. Q^2 quantifies the PLS model's capability to capture inter-variable relationships and its suitability for predictive and forecasting purposes. A higher Q^2 score signifies enhanced predictive relevance, signifying the model's reliability in predictions and its potential to generalize effectively, vital for applying the PLS model in practical real-world contexts. To conduct predictive relevance, this study used blindfolding technique which is a sample re-use technique. It systematically deletes data points and provides a prognosis of their original values. For this purpose, the procedure requires an omission distance D. A value for the omission distance D between 5 and 12 is recommended in literature (Hair et al., 2017). The result generated from blindfolding process on the model is as in table 8.

Table 8 - Generated results of predictive relevance

Constructs	SSO	SSE	Q^2 (=1-SSE/SSO)
IWT	1990	1990	
OIC	1990	1990	
OP	1990	1251.486	0.371
PAK	1990	1990	

Results from table 8 presents the Sum of Squares Explained (SSO) and Sum of Squares Error (SSE) for each construct in the model, as well as the corresponding Q^2 values, which indicate predictive relevance. For the construct OP, the SSO is 1990, and the SSE is 1251.486, resulting in a Q^2 value of 0.371. This Q^2 value signifies that the model has moderate predictive relevance for the construct OP, indicating that around 37.1% of the variance in OP can be predicted by the model. The SSO and SSE values for the other constructs (IWT, OIC, and PAK) are all the same at 1990, suggesting that the model perfectly explains the variance in these constructs during the blindfolding process, resulting in Q^2 values of 1 for these constructs. This indicates that the model has excellent predictive relevance for IWT, OIC, and PAK, and it can fully account for the variance in these constructs.

5.4 Bootstrapping

Bootstrapping is employed to facilitate hypothesis testing within the PLS model, aiming to assess relationships between constructs. This technique involves generating subsamples by randomly selecting observations from the original dataset (with replacement), and these subsamples are utilized to estimate the PLS path model. This procedure is iterated numerous times, often around 10,000, to enable robust analysis and enhance the reliability of the outcomes (Hair et al., 2017).

For this study the generated model after bootstrapping process is as figure 3 and the results of testing three hypotheses related to the relationships between the constructs IWT, OIC, PAK, and the construct OP as in Table 9. Each row represents a specific hypothesis, with the corresponding values for the original sample (O), the sample mean (M), standard deviation (STDEV), T statistics (|O/STDEV|), and P-values (Hair, J.E. et.al. 2017).

Table 9 - Generated results of hypothesis testing

Relationships	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
IWT -> OP	0.287	0.28	0.096	2.98	0.003
OIC -> OP	0.127	0.134	0.095	1.347	**0.178**
PAK -> OP	0.394	0.390	0.110	3.583	0.000

Table 9 indicates that hypothesis "IWT -> OP," the original sample coefficient is 0.287, and the T statistics value is 2.98, which indicates a significant relationship. The corresponding P-value of 0.003 confirms the statistical significance of this path. Regarding the hypothesis "OIC -> OP," the original sample coefficient is 0.127, and the T statistics value is 1.347, resulting in a non-significant relationship. The P-value of 0.178 supports **the lack of statistical significance**, suggesting that the path from OIC to OP may not be significant. For the hypothesis "PAK -> OP," the original sample coefficient is 0.394, and the T statistics value is 3.583, indicating a highly significant relationship. The P-value of 0 further confirms the statistical significance of the path from PAK to OP

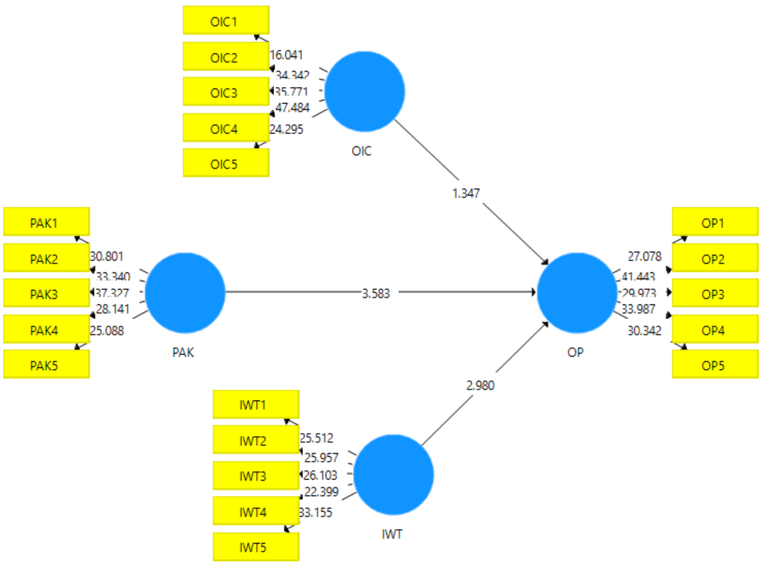

Fig 3 - Model after conducting bootstrapping (hypothesis testing)

6. Conclusion

This paper has presented the modelling of three technology innovation constructs namely Organization Innovation Capabilities; Potential Absorptivity Knowledge; and Interaction with Technology affecting the UAE Health Care organisation performance construct. The modelling processes was conducted in SmartPLS software using 398 data from employees of UAE public health care organization. Results from the modelling analysis found that model fitness criteria, which are Chi-Square value and NFI (Normed Fit Index) have an acceptable fit index. The model also has excellent predictive relevance for independent constructs that have fully account for the variance in dependent construct. however, one of the three paths was found not significant which is the path from OIC to OP [*Organization Innovation Capabilities to UAE Health Care organisation performance*]. In term of path strength, paths from the construct OP to IWT has coefficient value of 0.3; to OIC has coefficient value of 0.1; and to PAK has coefficient value of 0.4. It is hope that the findings from this study have contributed to the knowledge of the relationship between the technology innovation dimension affecting the UAE public health care organization.

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