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Mediation Model of Digital Technology Factors Affecting Health Care Service Performance

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Abstract: Healthcare technologies have become a crucial component of healthcare providers' daily operations. Hence, healthcare innovation technologies are being promoted worldwide. Healthcare service technologies are constantly improving necessitates ongoing research to show how these technologies affect healthcare services. Hence, current study investigating the state of innovative digital healthcare service practises in the UAE. It examining the effect of innovative technology on healthcare service performance in the UAE and modelling mediating role of organisational learning capacity in the relationship between innovative technology and healthcare service performance. A structural equation model was developed in SmartPLS software using the data collected of the questionnaire. The model showed that the factors system development, digital services, process integration, and IT base innovations have strong relationship effect to the health care performance. Also, the organisational learning capacity has strong mediation effect on the health services relationship. This research has contributed to current state of literature regarding digital service innovations related to health service performance in the UAE. The results emphasized a critical need for practitioners for promoting developments in digital services impacted the performance of health services.

Keywords: Health care, service practice, technology, innovation

1. Introduction

Finding a solution involving cutting-edge medical technologies will be necessary in a time when medical care faces numerous challenges, such as the declining number of doctors in the world and the failure to keep up with the changes and rapid progress in the medical world, without forgetting other changed elements like culture and human factors. Under the umbrella of "digital health," cutting-edge medical technologies, quick innovation, and digital communication have gradually merged to offer the best healthcare services. So what precisely is digital health? "The cultural transformation of how technologies that provide digital and objective data accessible to both caregivers and patients leads to an equal level caregiver-patient relationship with shared decision-making and the democratisation of care," according to the definition of digital health (Mesko, 2018).

We suggest a new method for determining factors that influence the acceptance and resistance of new technologies by medical staff and patients in light of the observation that hospitals and centres have resisted these technologies (Kumar et al., 2020). In contrast to modern medicine, which is based on the individual and partnership where the point of care is the patient himself and the costs are covered by Moore's Law (1975), traditional medicine is very expensive and is based on population and hierarchy, with the point of care being the lab or clinic itself rather than the patient. By

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their very nature, health care services demand behavioural change from both the providers and recipients of the care, and this cannot be imposed. No single group, organisation, or government has the power to directly influence someone's behaviour. Both internal and external impulses are possible, and both have a variety of effects.

According to the UAE's 2021 Vision, "the UAE will continuously invest to build world-class healthcare infrastructure, consolidate all experiences, and provide services in order to meet the evolving needs of citizens. The United Arab Emirates has a sizable wealth from oil revenue and a relatively small population, so it was able to research best practises and the newest technologies and put them into practise without getting bogged down by the conventional wisdom. This technological advance allowed it to swiftly advance through several stages of technological development and put the newest healthcare technologies into use. The government's concern for the nation's citizens' health and welfare served as the primary impetus for this. They have been able to do this fairly easily and are still doing so thanks to sufficient wealth, a small population, and young people who are generally too eager to adopt new technology (Owuor, 2019). The Ministry of Health and Prevention, Dubai Health Authority (DHA), Abu Dhabi Health Authority (HAAD), Dubai Healthcare City Free Zone, and the Emirates Health Authority are just a few of the regulatory bodies that oversee public healthcare in the United Arab Emirates (EHA). Each of them is in charge of facilities, physician, pharmacist, and other medical specialty licencing. Although it is not the only player in the UAE healthcare system, the Ministry of Health plays a significant role in providing healthcare (Arnold, 2020). The goal of the current study is to create a framework for analysing how innovative digital healthcare technologies affect the performance of healthcare services. The goal of this paper is to create a model of innovative digital healthcare service practises in order to improve the performance of healthcare services. All other non-health organisations were not included in the study because it was only conducted in government hospitals in the United Arab Emirates. Since they are the ones who make decisions regarding the application of new healthcare digital technology innovations, managerial and operational staff in health organisations were involved in data collection. The other employees of healthcare organisations are not included in this. By concentrating on four key categories of the factors i.e. System Development (SD), IT Base Innovations (BIN), Technology Services (TS), and Process Integration, it measured the effect of innovative digital technologies on the health sector (PIN).

2. Literature Review

2.1 Digital Technology and Healthcare Performance

A health service is any service that attempts to promote health or to diagnose, treat, and rehabilitate patients, including but not limited to medical or clinical services (World Health Organization, 1998). The term "healthcare services" refers to the provision of patients, families, communities, and residents with health services by medical professionals, institutions, and assistive healthcare personnel. These services include home care, palliative care, long-term, hospital, preventive, rehabilitative, preventive, diagnostic, and emergency care. These services emphasise patient-centeredness, improving quality, and patient access to healthcare. Effective health care delivery requires a variety of caregivers and services (The World Health Report, 2000). The provision of treatment, care, advice, instruction, services, or other supplies related to the health or death of a person or population, with the capacity to respond to emergencies, is referred to as providing healthcare services. It also refers to the assistance offered by medical professionals like doctors, nurses, and medical therapists, as well as by health initiatives and nursing facilities. They include alcoholism, substance abuse, and mental health services, as well as clinically relevant services (preventive, diagnostic, curative, rehabilitative, and palliative).

A health system consists of all activities that aim to enhance, restore, and/or maintain health (Arlington, 2020). According to the definition given in the World Health Report from 2000, a health system is a grouping of people, organisations, and resources that are brought together in accordance with specific policies and regulations to promote the health of the people it serves. It also responds to people's legal perceptions and shields them from needless expense by defining specific activities with a primary focus on promoting health. Any effort to promote health, including self-care, public health services, and collaborative initiatives (The world health report, 2000). By incorporating technological advancements into the system, the health care system can be effectively implemented across a wider spectrum. Technology is a collection of procedures, techniques, know-how, and practical applications of scientific knowledge in many fields of our daily lives. It can be very straightforward or extremely complex, and it comes in a variety of forms. Mechanical technology is one type and includes engines, wheels, belts, and cams. Electronic technology, more commonly known as electronics, is perhaps the category of technology with which we are most familiar today (Fitzgerald et al., 2014).

The term "digital technology" refers to all forms of electronic devices and software that use digitised data in the form of binary code, which consists of the two numeric characters 0 and 1, also known as bits, to represent words and images. Information technology and computer science are both incorporated into digital technology. It makes it possible to pack enormous amounts of information onto compact storage devices that are simple to store and transport. Data transmission speeds are accelerated by digitization.

2.2 Healthcare Performance

Health care performance, which connects and evaluates numerous organisational aspects like quality, efficiency, effectiveness, direction of information, progress, and financial aspects, is one of the challenges that health care services generally face (Nur et al., 2015). Every stakeholder in healthcare, including patients, administrators, health service providers, governments, insurance companies, and other payers, has the opportunity to improve decisions through performance appraisal. Although there has been significant progress in measuring healthcare performance due to the development of information technology and a growing emphasis on patient choice and healthcare accountability, health organisations still need to significantly expand data collection and analysis, policy making, and strategic planning. Healthcare performance covers a wide range of topics (including patient health, treatment outcomes and productivity, quality and suitability of care, responsiveness and fairness, and various other aspects) (Smith et al., 2009; Antes et al., 2021).

2.3 Effect of Digital Health Services on Healthcare Performance

Healthcare continuously improves its capacity to foster health workers' productivity, enhance the delivery of health services, and increase patients' capacity to pay for traditionally provided healthcare costs. The need to create them grows over time as technology makes it easier to provide health services, improves communication between patients and doctors, and makes life more effective (Sahu et al., 2014). Al-Ansari, Altalib, and Sardoh (2013) examined how innovation and technology are combined and how this affects workplace productivity, particularly in Dubai, United Arab Emirates. The study, which was conducted in 200 different sized companies in Dubai, revealed that technological trends had an impact on innovation but not performance in a significant or obvious way. Instead, innovation had an impact on job performance. The findings showed that in order to achieve excellent job performance, company managers must view innovation as a technology intermediary. According to Kohli and Tan (2016), information technology may have an impact on institutional performance by increasing productivity, boosting earnings, lowering costs, and reducing inventories. It may also prove to have an impact on how well health organisations, patients, and suppliers communicate with one another. Electronic health records (EHRs) are an illustration of technology used in the healthcare industry. The importance of EHRs is to combine the patient's medical history with the treatment he is currently receiving, which results in improving the quality of healthcare and its productivity.

The outcomes of the IT developments have emerged as a crucial issue, and businesses are considering how to integrate them with other institutional activities. It has been demonstrated that IT significantly affects customer satisfaction and raises quality. However, the researchers were unable to definitively establish a link between performance and information technology. When implementing specific initiatives, IT performance results may be accurate, but this requires variable control and a long amount of time (Devaraj and Kohli, 2000).

2.4 Organisational Learning Capacity

Several research studies have emphasised the importance of socio-technical dimensions in evaluating healthcare technology implementations (Hsiao et al., 2011; Ash et al., 2012; Hameed et al., 2012; Cresswell and Sheikh, 2014). According to Cresswell et al. (2012), disruptive technological advancements in healthcare offered a singular opportunity to recognise and examine the changing inter-relationships between technology and human/organizational variables.

Future healthcare system delivery was categorised as a wicked challenge by Westbrook et al. (2007) due to its ill-defined and uncertain nature related to significant moral, political, and technical concerns. They argued that a focus on the larger organisational and environmental context and processes in implementation studies is necessary to address the dynamic relationship issues that arise in an emergent social setting. With a focus on organisational and human (socio) factors, numerous hypotheses are increasingly being used to better understand the factors that influence the performance of healthcare innovation system implementation (Cresswell and Sheikh, 2014).

In earlier research studies, organisational learning capacity (OLC) was looked at as an organisational trait connected to the effectiveness of technology implementation (Khamis et al., 2014). Organizational learning is the process by which organisations modify or adapt their theoretical frameworks, rules, practises, or domain knowledge in order to maintain or enhance their performance (Chiva et al., 2014). Huber (1991) described organisational learning as a dynamic process that moves between various action stages, from individual to group to organisational, before turning around. According to Huber (1991), this kind of organisational learning need not be deliberate or intentional; a person learns if the range of potential actions changes as a result of processing new information. The ability of an organisation to implement appropriate management practises, structures, procedures, and policies that encourage and foster learning is known as organisational learning capacity. Alerasoul et al. (2021) assert that an organization's learning capacity should be able to create, acquire, transmit, and incorporate new information as well as modify current practises in order to increase output by accounting for new knowledge.

The amount of research on the various aspects of organisational learning capability has increased over the years. Early models to evaluate the maturity of an organization's learning capacity used learning curves, experience curves, a range of patents, and research expense budgets for organisations (Jerez-Gomez et al., 2005). Academics have described the application of technology as the operationalization of an invention. The relationship between technology innovation and technology implementation performance has been the subject of several studies (Khamis et al., 2014; Uğurlu and Kurt, 2016). Robey et al. (2002) examined the relationship between organisational learning capacity (OLC) and the introduction of a technology-based innovation like enterprise resource planning in a study of 13 industrial companies (ERP). After reviewing comparative case studies, they came to the conclusion that OLC was crucial in removing knowledge barriers related to the implementation of the system. Ke and Wei (2006) looked into how organisation learning capability (OLC) affected the performance of ERP system implementation in China. They found that OLC has an effect on implementation performance. In a study, Tucker et al. (2007) examined how an organization's capacity for learning affected the efficacy of a technology-based continuous improvement strategy used in an intensive care unit. According to empirical research, the Learn-how construct of organisational learning capability, which focused on elements related to operationalizing modern processes, was positively correlated with the effectiveness of the plan's implementation.

Based on Sundbo's theory of strategic management of innovation, Mat and Razak (2011) proposed a conceptual research model to investigate the relationship between organisational learning capacity factors and technology innovation implementation performance that is moderated by the knowledge complexity inherent in an innovation (Sundbo, 2001). Organizational learning capacity is crucial throughout the innovation lifecycle, from concept creation to successful implementation (Alerasoul et al. 2021). The effect of organisational learning capacity on the advancement of e-Business implementation was examined by Khamis et al. in 2014. Based on data gathered from 110 organisations in the Malaysian banking and financial services industry, t was found that organisational learning capacity constructs have a significant positive association with effective eBusiness implementation. Uğurlu and Kurt (2016) addressed the impact of organisational learning capacity on product innovation performance in the Turkish manufacturing industry.

Organisational learning capacity precedes organisational change, which in turn affects how successfully technology is adopted. It has been demonstrated that an organization's capacity for learning influences how quickly new technologies are adopted. This understanding is consistent with earlier academic studies that discovered organisational learning capacity to be one of the most crucial elements affecting the performance of newer technologies and process implementation (Khamis et al., 2014; Alerasoul et al., 2021). This demonstrates that organisational learning capacity is the primary factor that contributes to an organization's improved performance, particularly when technology innovation practises are applied. Therefore, in healthcare organisations, the relationship between service performance and technology innovation practises can be mediated by organisational learning capacity. There is still a need for the current study to fill in the investigation of organisational learning capacity as a mediator between digital technology innovations and healthcare performance.

2.5 Conceptual Framework and Hypothesis Development

It is possible to investigate digital technology practises using a variety of models. One of the popular models was developed by Lyytinen and Rose in 2003 and focused on the innovative use of digital technology in organisations. According to Lyytinen and Rose (2003), system development, digital technology innovations of organization services primarily includes four factors which are system development; using digital tools and services to carry out daily operations; using IT base innovations, and interdepartmental process integration. The first factor system development describes the process of giving the organization's existing system processes new capabilities. By incorporating new features, fixing system flaws, and enhancing the functionality of the current system, system development contributes to the enhancement and improvement of the organization's system (Mutie, 2018). The system development factor typically seeks to enhance organisational effectiveness, reduce costs, satisfy regulatory requirements, increase system efficiency, and make use of emerging technologies (Kash and Rycroft, 2002). An operational analysis can be used to determine whether the system needs to be developed and how much funding will be needed to use new technologies to address any problems with the organization's system processes (Dodgson and Gann, 2011). As a result, it is assumed that:

H_1: System development has a significant impact on healthcare service performance.

Utilizing IT-based innovations, such as new software, hardware, and services, constitutes the second factor. IT base innovations can include (i) updates to the underlying technology, which deals with functionality, responsiveness, and other features, (ii) enhancing the functionality of current systems, and (iii) alterations to the features of the services. The IT base innovations are developing quickly and are becoming crucial for gaining competitive service operations by turning opportunities into fresh concepts (Lin and Hu, 2007). In other words, IT base innovations enable the company to maintain sustainable service competitiveness while surviving in universally changing circumstances. As information technologies advance and new ones emerge periodically, there are numerous IT-based innovations available. Examples include mobile Internet, the Internet of Things, quantum computing, big data, artificial intelligence, and other information technologies (Kang and Wang, 2020). Therefore, it is hypothesised that

H_2: Technology services have a significant effect on healthcare service performance.

The use of digital tools and services for routine tasks and internal firm communication constitutes the third factor, which is technology services. Technology process innovation, technology service innovation, and technology integration innovation are all examples of service innovations. Use of digital services has the benefit of increasing services' long-term effectiveness by reducing wait times and streamlining organisational procedures. Digital tools can facilitate collaboration within an organisation and aid in the management of documents, human resources, customer relationships, and internal processes (Kash and Rycroft, 2002). Mutie (2018) claims that using digital tools within an organisation can enhance customer relationship management and human resource management. Employees in various locations can communicate effectively thanks to the intranet. To manage customer relationships effectively, methodically, and profitably, customer management tools are used. Tools for human resource management help the organisation manage employees to perform to the best of their abilities and to assess their performance. The third hypothesis is thus as follows.

H_3: IT-based innovation has a significant positive impact on healthcare service performance.

The inter departmental process of integration is the fourth factor, which is adapted from the previous service factor. In order to complement and collaborate with other departments' work in order to meet standards and deliver better services, it is crucial for departments within an organisation to work together (Mutie, 2018). Additionally, effective inter departmental process integration is a crucial management tool for striking a balance between operational efficiency centralization and decentralisation throughout the entire organisation with the aim of achieving the organization's objectives (Tidd and Bessant, 2020). On the basis of the discussion above, the following is hypothesised:

H_4: Process integration has a significant effect on healthcare service performance.

The capacity for learning within an organisation can be described in a variety of ways. According to Levinthal and March (1993), it is the accumulation of individual, small-group, and collective learning that exists within an organisation and has the potential to affect the success of the organisation (Goh, Chan, and Kuziemsky, 2013). Additionally, it is described as a system-level phenomenon that endures in the organisation despite changes in the health care teams or groups and as a mechanism for enhancing organisational effectiveness and productivity through shared understanding (Peirce, 2000; Ratnapalan and Uleryk, 2014). To put information into action and analyse those actions in order to develop shared knowledge within an organisation, teams and team members can be thought of as having updated context-specific learning skills. Because these learnings frequently take place in professional or group silos with little to no information exchange with other groups within the organisation, individual and team learning support organisational learning but do not deliver it.

The importance of organisational learning in healthcare systems is that it lays the groundwork for dynamic, complex systems where all operating units are required to learn their specific roles and perform them in order to maximise patient safety as a whole. Healthcare organisations develop procedures and policies to reduce errors and improve patient safety. As continuing education has been associated with better patient outcomes, licenced health practitioners are required to participate in it to maintain and upgrade their knowledge and skills in order to provide secure patient care (Davis and Galbraith, 2009). Contrarily, while many organisations provide and plan for continuing professional development to boost productivity at the individual or local level, there is no explicit requirement for support or administrative staff members in healthcare institutions to take part in continuing education (Ratnapalan and Uleryk, 2014). Organizational learning serves as the foundation for integrating these various organisations and mandates into a seamless structure to advance healthcare services. Even though organisational learning capacity has been discussed across a range of industries, there aren't many studies looking into how it might mediate the connection between technological advancements and service effectiveness in healthcare organisations, at least not in the UAE.

The conceptual framework of the current study is presented in Figure 1 below.

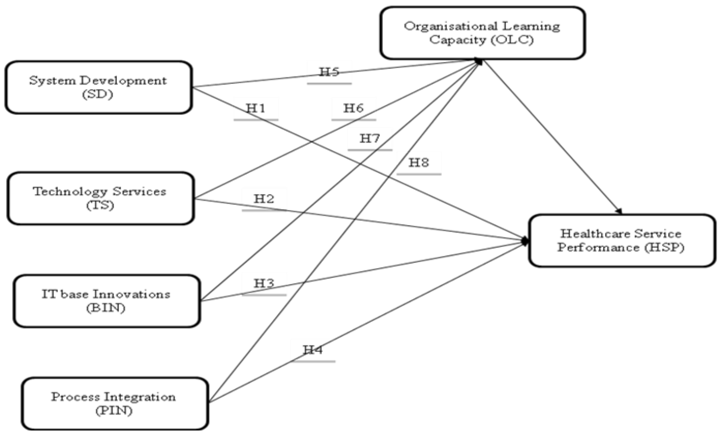

Fig. 1 - Conceptual framework

In essence, based on the research conceptual framework as in Figure 1, several hypotheses were developed as:

H_1: System development has a significant impact on healthcare service performance.

H_2: Technology services have a significant effect on healthcare service performance.

H_3: IT-based innovation has a significant positive impact on healthcare service performance.

H_4: Process integration has a significant effect on healthcare service performance.

H_5: Organizational learning capacity has a positive mediating role between system development and healthcare service performance.

H_6: Organizational learning capacity has a positive mediating effect on the relationship between IT base innovations and healthcare service performance.

H_7: Organizational learning capacity has a positive mediating effect on the relationship between technology services and healthcare service performance.

H_8: Organizational learning capacity has a positive mediating effect on the relationship between process integration and healthcare service performance.

Several attributes were identified to measure the categories of the factors. These attributes measuring the factors were identied through literature review as shown in Table 1.

Table 1 - Attributes of various factors

No.	Statements	Source
System Development		
1.	The organization frequently improves the effectiveness of the existing system.	Lyytinen and Rose (2003); Mutie (2018); Rycroft and Kash, 1999); Dodgson and Gann (2011)
2.	The organization updates the technological features of existing system to improve healthcare services.	
3.	The organization continuously corrects the identified defects in its system.	
4.	The organization modifies the existing system on a continuous basis to enhance its efficiency.	
5.	The organization adopts new technology advancements to improve the organization processes.	
6.	Our organization tries to improve its services through improving the existing system.	
IT Base Innovation		
7.	The organization frequently adds new capabilities to the existing system.	Lyytinen and Rose (2003); Mutie (2018); Lin and Hu (2007); Kang and Wang (2020)
8.	New features are often added to the existing system.	
9.	The organization has automated storage and retrieval system.	
10.	The organization continuously improves the speed of the existing service system.	
11.	The organization focuses on the reliability of the service system.	
12.	The organization makes use of advanced technological functions in our service system.	
13.	Our organization follows up-to-date technological services.	
14.	Our organization is interested in improving technological processes to provide better services to patients.	
Technology Services		
15.	The organization is connected with an intranet.	Lyytinen and Rose (2003); Mutie (2018); Kash and Rycroft (2002)
16.	The organization is connected with an extranet.	
17.	The organization has an efficient human resource management system.	
18.	The organization has an efficient customer relationship management system.	
19.	The organization has an effective medicine distribution system.	
20.	All the departments are connected with the organization technology system.	
21.	Our organization is interested in adopting new technological services.	
Process Integration		
22.	There is continuous online interaction between departments.	Lyytinen and Rose (2003); Mutie (2018); Kash and Rycroft (2002);
23.	There is efficient flow of information between functions and departments.	
24.	Online collaboration among departments is encouraged in the	

	organization.	Tidd and Bessant (2020)
25.	All departments use their online functions to achieve the organization goals.	
26.	Electronic data interchange is widely practiced in the organization.	
27.	Employees can easily request data from other departments.	
Organizational Learning Capacity		
28.	Our organization encourages employees to attend training sessions to acquire new knowledge.	Adapted from Kordab, Raudeliūnienė and Meidutė-Kavaliauskienė (2020)
29.	Our organization considers employees learning as an investment in human development of the organization asset.	
30.	Our organization encourages employees to practice the learning they acquire.	
31.	Our organization has broad training processes where employees can share knowledge.	
32.	Our organization encourages employees to continue their education, which will be a benefit to the organization.	
33.	Our organization make training sessions to improve employees' skills to use technology in their work.	
34.	Our organization encourages employees to give innovative ideas to improve the hospital services.	
Healthcare Service Performance		
35.	Compared with other health organizations, our healthcare service is more successful.	Adapted from Akram, Goraya, Malik, and Aljarallah (2018)
36.	Compared with other health organizations, our healthcare service is more advanced technologically.	
37.	Compared with other health organizations, our healthcare service is faster.	
38.	Compared with other health organizations, our healthcare service is more innovative.	
39.	Our healthcare service workflow is easier.	
40.	Our digital healthcare services make the process easier for our customers.	
41.	Digital technology has made the service of our organization more efficient.	

3. Research Methodology

Research is a task that facilitates data collection or description writing. Gathering data is the first step in any research project. For analysis to yield accurate and logical results, data collection entails gathering accurate information with the least amount of distortion (Sapsford and Jupp, 2006). The questionnaire is one of the most useful and well-known methods for gathering data. The advanced multivariate analysis technique known as structural equation modelling was used to investigate research questions through quantitative analysis. A framework for describing the relationship between a number of unobservable variables (constructs) and observed variables is the structural-equation model (SEM). Unobserved (latent) variables are those that cannot be measured directly but are dependent on the factors that affect them. Observed variables are those that can be calculated directly. Using structural equation modelling (SEM), researchers can quickly determine the relationship between observed variables and latent variables (unobserved) (Okech et al., 2015).

SEM is widely used in the social sciences, biology, building engineering, and economics. This method of multivariate statistical analysis can be applied to look into structural relationships. A tool called SEM can be used for both exploration and confirmation. Every path model in SEM is composed of the structural model, or inner model, and the measurement model, or outer model. The connections between latent variables are the focus of the structural model. On the other hand, the measurement model addresses the connections between latent variables and their manifestations (Abusafiya et al., 2017). The focus is on SEM because it is a potent method that can analyse models with imperfectly measured variables and it can solve many research issues in the engineering and construction fields (Molenaar et al., 2000). SEM also significantly contributes to the development of science across a range of disciplines. Many researchers have used SEM in their work, and it has proven to have many benefits in terms of prediction and theory growth. For example, Memon et al. (2013) assessed effects of construction resource factors on cost overrun. Rahman et al (2014) used SEM to model causes of cost overrun in large projects of Malaysia. Durdyev et al. (2018) used SEM to examine client satisfaction of service quality using a developed theoretical framework. Almansoori et al. (2021) developed Relations between factors affecting PMO. Khahro et al. (2021) used SEM for studying Green Procurement in the Pakistan. Rahman et al. (2022) modeled Causes and Effects of Construction Changes for UAE Construction with SEM. Memon (2013) pointed out that PLS approach of SEM is more relative and benefitial in exploratory research as compared of covariance based SEM approach which can be used for confirmatory research aspect. Hence, this study adopted PLS-SEM because the current research is an exploratory study to develop a model for explaining the impact of healthcare digital technology on service performance in the UAE.

4. Demography of the Respondents

The demographic information provides a description of the characteristics of the study sample. There are 200 valid responses in total, which is sufficient for SEM data analysis (Awang, Z. 2012). The study's participant background information includes age, years of experience, and educational level. It was found that 26.2% of respondents are aged between the ages of 20 and 30; 33.5% are between the ages of 31 and 40; 20.4% are between the ages of 41 and 50; 14.1% respondents are between the ages of 51 and 60; and 5.8% are older than 60. In terms of gender, males make up 44% of the population while females make up 56%. Analysis of demographic data reveals that 44.7% respondents have worked with health organisation for one to five years, 32% respondents have worked there for six to ten years, 16% have worked there for eleven to fifteen years, and 7.3% have worked there for more than sixteen years in health organisation. Participants with a diploma make up 1% of the total, those with a bachelor's degree make up 60%, those with a master's degree make up 30%, and those with a Ph.D. make up 8%.

5. Model Development through PLS-SEM

5.1 Measurement Model Assessment

PLS-SEM allows step wised analysis where prior to assessing the structural model, the measurement models are tested adhere to a set of quality standards. First step of the analysis is assess the validity of the measurement model. Convergent and discriminant validity are the two types of validity that take a look at the outer model of the research items (Hair et al., 2014). Convergent validity is produced by examining the factor loadings of indicators and computing the Average Variance Extracted (AVE). The measurements demonstrate the capacity of the variance measurement models for the indicators (Wong, 2016). The Fornell and Larcker criteria, as well as the cross-loading of the outer models, are used to assess the measuring models' discriminant validity.

Reliability is the extent to which a scale produces consistent and stable measures over time, and it is related to reflecting characteristics of the measurement model (Hair et al., 2014). Reliability is a measure of how free the scale is from random errors and describes the extent to which measuring scale responses are consistent across constructs (Pallant, 2011; Creswell, 2014). When dealing with PLS-SEM, composite reliability is preferred even though Cronbach's alpha is the most frequently used reliability metric (Awang, 2012). (Hair et al., 2011; Wong, 2016). For a measurement model to be regarded as reliable, its composite reliability must be at least 0.7. (Wong, 2013). But for recently built scales, a composite reliability of 0.6 is also thought to be sufficient for proving reliability (Chin, 1998, Hair et al., 2011, Bagozzi and Yi, 1988). The techniques for evaluating model validity and reliability are shown in Table 2.

Table 2 - Constructs' outer loading

Construct	BIN	HSP	OLC	PIN	SD	TS
BIN1	0.625					
BIN2	0.825					
BIN3	0.823					
BIN4	0.749					
BIN5	0.841					
BIN6	0.86					
HSP1		0.671				
HSP2		0.763				
HSP3		0.77				
HSP4		0.727				
HSP5		0.794				
HSP6		0.72				
OL1			0.833			
OL2			0.864			
OL3			0.84			
OL4			0.803			
OL5			0.831			
PIN1				0.74		
PIN2				0.715		
PIN3				0.762		
PIN4				0.723		
PIN5				0.775		

PIN6				0.771		
SD1					0.723	
SD2					0.782	
SD3					0.812	
SD4					0.85	
SD5					0.778	
TS1						0.812
TS2						0.754
TS3						0.775
TS4						0.647
TS5						0.852
TS6						0.819

Table 2 shows that all of the outer loadings for all of the values are greater than 0.7 except BIN1, HSP1, and TS4. The analysis excludes these three items. By excluding BIN1, HSP1 and TS4, the model was re-run and the results of convergent validity parameters to test the reliability are presented in table 3.

Table 3 - Convergent validity

Constructs	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
BIN	0.878	0.909	0.626
HSP	0.836	0.88	0.551
OLC	0.891	0.92	0.696
PIN	0.843	0.884	0.559
SD	0.849	0.892	0.624
TS	0.872	0.902	0.607

The table 3 reveals that Cronbach's Alpha value of all the factors exceeds 0.7 which is the desired value. The composite reliability of all the factors is also higher than 0.7 and the AVE values exceed the suggested values of 0.5. As a result, each measurement model complied with the requirements for convergent validity. Hence, the model is assessed for discriminant validity.

Discriminant validity assesses how much a measurement model differs from other study constructs. It evaluates how one measurement model differs from other models in the structural model (Memon and Rahman, 2013). When evaluating discriminant validity, the Fornell and Larker criterion and the Cross-loading criterion are frequently employed. Fornell and Larcker's (1981) criterion for showing discriminant validity states that the square root of each measurement model's AVE must be greater than the correlation of the model with any other model in the structural model. Therefore, in the current study's Fornell and Larker's test, the square root of each outer model's AVE should be higher than its correlation with any other construct (Hair et al., 2014). A discriminant validity test developed by Fornell and Larker is displayed in Table 4.

Table 4 - Discriminant validity results based on Fornell–Larcker criterion

Constructs	BIN	HSP	OLC	PIN	SD	TS
BIN	**0.84**					
HSP	0.694	**0.772**				
OLC	0.612	0.706	**0.834**			
PIN	0.482	0.593	0.703	**0.747**		
SD	0.71	0.59	0.745	0.636	**0.79**	
TS	0.639	0.626	0.76	0.737	0.782	**0.808**

Table 4 reveals that the Fornell–Larcker criterion is confirmed. The second assessment of discriminant validity is the cross-loading test. Cross-loading criteria states that items must load more heavily on their underlying constructs than their cross-loading on other constructs (Hair et al., 2014; Wong, 2016). Each factor in the current study had a stronger cross loading on itself than the other factors, as shown in Table 5, indicating discriminant validity.

Table 5 - Cross-loading assessment

Constructs	BIN	HSP	OLC	PIN	SD	TS
BIN2	**0.844**	0.575	0.558	0.4	0.635	0.559
BIN3	**0.849**	0.572	0.507	0.401	0.64	0.529
BIN4	**0.79**	0.521	0.419	0.3	0.519	0.369

BIN5	**0.861**	0.606	0.509	0.403	0.566	0.546
BIN6	**0.855**	0.633	0.563	0.502	0.617	0.649
HSP2	0.54	**0.761**	0.609	0.465	0.436	0.526
HSP3	0.623	**0.783**	0.611	0.52	0.566	0.572
HSP4	0.467	**0.73**	0.463	0.464	0.361	0.391
HSP5	0.532	**0.826**	0.558	0.459	0.491	0.506
HSP6	0.495	**0.755**	0.453	0.361	0.393	0.383
OL1	0.637	0.682	**0.833**	0.532	0.637	0.608
OL2	0.488	0.586	**0.864**	0.635	0.6	0.604
OL3	0.439	0.624	**0.839**	0.72	0.607	0.691
OL4	0.521	0.521	**0.803**	0.521	0.609	0.564
OL5	0.462	0.514	**0.831**	0.504	0.553	0.591
PIN1	0.459	0.504	0.585	**0.743**	0.531	0.617
PIN2	0.394	0.537	0.605	**0.719**	0.513	0.683
PIN3	0.234	0.359	0.466	**0.758**	0.443	0.524
PIN4	0.367	0.412	0.479	**0.721**	0.437	0.439
PIN5	0.228	0.346	0.472	**0.771**	0.472	0.511
PIN6	0.422	0.44	0.492	**0.77**	0.426	0.467
SD1	0.528	0.515	0.655	0.51	**0.723**	0.604
SD2	0.496	0.384	0.543	0.466	**0.782**	0.542
SD3	0.593	0.48	0.57	0.514	**0.811**	0.694
SD4	0.633	0.493	0.583	0.509	**0.851**	0.669
SD5	0.544	0.435	0.57	0.504	**0.777**	0.564
TS1	0.529	0.408	0.518	0.501	0.6	**0.814**
TS2	0.469	0.349	0.484	0.422	0.562	**0.75**
TS3	0.506	0.447	0.521	0.549	0.683	**0.762**
TS5	0.573	0.611	0.612	0.694	0.683	**0.869**
TS6	0.504	0.622	0.648	0.619	0.632	**0.837**

In table 5, bold values indicate the loadings of the items on their structures. The results demonstrate that everything loads its underlying constructions more heavily than it loads other constructs cross-wise. Therefore, based on this criterion, the measurement models achieve discriminant validity. Figure 2 shows the final measurement model satisfying the convergent and discriminant validity.

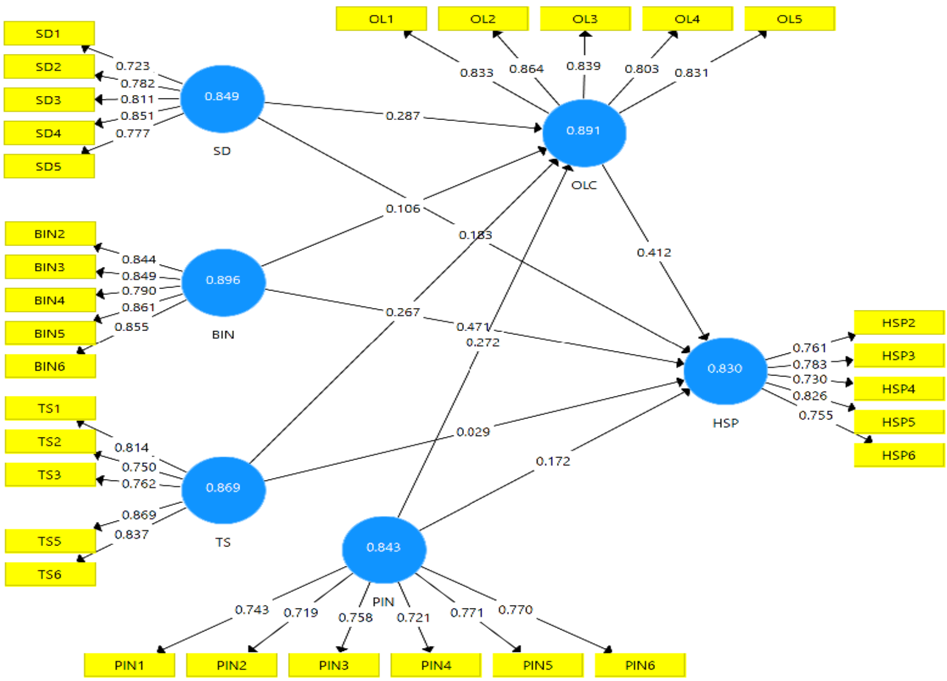

Fig. 2 - Assessment of measurement model through PLS algorithm

5.2 Structural Model Assessment

The structural model establishes the causal relationships between the measurement models (Hair et al., 2014). The connections that are described here are meant to answer research questions and validate research hypotheses. The main goal of structural model evaluation is to assess the model's accuracy and predictability of endogenous constructs. The path coefficients and their significance, the endogenous construct's coefficients of determination (R^2), the effect sizes of the exogenous measurement model (Cohen's f^2), the model's predictive relevance (Q^2), and its overall goodness of fit (GoF) are all evaluated using the bootstrapping procedure (Hair et al., 2011; Hair et al., 2014; Wong, 2016).

5.2.1 Coefficient of Determination (R2) Assessment

Coefficient of determination (R^2) metric for the value of the structural model which measures the amount of variance explained by the model. The total exogenous construct contribution to explaining or forecasting the variance of the endogenous construct in the structural model is shown by the coefficient of determination, also known as R^2. The quality of the model increases as more variance is predicted or explained, and vice versa (Hair et al., 2011; Hair et al., 2014; Wong, 2016). However, a number of researchers have provided recommendations for what is reasonable, which vary by discipline, despite the lack of standardised standards for determining how much R^2 is acceptable. R^2 values of 0.25, 0.50, and 0.75, for instance, are considered poor, average, and significant, respectively (Hair et al., 2014; Wong, 2016). According to Hair et al., (2014) an R^2 value of 0.2 is regarded as high in the study of consumer behaviour. Rahman et al. (2013) cited that the model is weak at R^2 of 0.02, moderate at 0.13 and substantial if R2 reaches to a value of 0.26. The R^2 for the final model is shown in table 6.

Table 6 - R^2 evaluation

Dependent/mediation variables	R^2 Square	R Square Adjusted
HSP	0.629	0.62
OLC	0.673	0.666

Table 6 displays the R^2 coefficients of Performance of health services is 0.620, while organisational learning capacity has an R^2 of 0.666. Hence, the model can be reported as substantial.

5.2.2 Effect Size (F^2) Evaluation

R^2 withholds information about how external structures affect people. Although route coefficients show the individual influence of each path in the structural model and R^2 shows the total contribution of all exogenous constructs to variance prediction, they do not show the relative contribution of each exogenous construct to R^2. Calculating the individual contributions of each external component to the R^2 is done using the effect size (f^2) (Hair et al., 2011). Chin (1998) suggested to compute impact size, calculated by estimating changes in the R-squared, represents the relative impact of various exogenous constructions on endogenous constructs (s). The effect size of each construct in the structural model is determined using Cohen's f^2. The formula operates by taking a specific construct out of the model and evaluating the results (Hair et al., 2014).

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

Where:

f^2 = effect sizes
R^2 incl = R^2 inclusive (R^2 with a particular construct included in the model)
R^2 excl = R^2 excluded (R^2 with a particular construct excluded from the model)
1= Constant

According to Cohen (1988), a low effect size is denoted by $f^2 = 0.02$, a medium effect size is denoted by $f^2 = 0.15$, and a high effect size is denoted by $f^2 = 0.35$. The effect sizes of various research constructs were examined using the criteria listed above, as shown in table 7.

Table 7 - Effect sizes (f^2)

Constructs	f^2	Effect size
BIN	0.281	Moderate
OLC	0.15	Moderate
PIN	0.032	Small
SD	0.026	Small
TS	0.18	Moderate

According to the values in the table 7, there is a significant impact of personal and policy factors, a moderate impact of process factors, and a small impact of technical factors. The results show that the exogenous constructs complied with f^2 standards.

5.2.3 Predictive Relevance (Q2) Assessment

To evaluate the structural model's predictive value, cross-validated redundancy is used. The data points for all indicators were examined using stone-predictive Geisser's relevance (Q^2) to determine whether all indicators in the outer model of endogenous constructs could be accurately predicted (Wong, 2016). The sample re-use methodology is used in this approach, which entails omitting a portion of the data matrix, estimating model parameters, and forecasting the remaining portion using the estimated model parameters (Hair et al., 2011; Hair et al., 2014). This quality evaluation criterion requires the cross-validated redundancy (Q^2) value to be a positive integer greater than 0 in order to have an effective predictive relevance (Chin, 1998).

The study's final models are assessed based on the aforementioned submission using the blinding method and Smart-PLS software to determine cross-validated redundancy (Q^2) (Ringle, Wende and Becker, 2015). Table 8 displays the results of the method using blindfolds.

Table 8 - Predictive relevance

Dependent/mediation variables	SSO	SSE	Q^2 (=1-SSE/SSO)
HSP	1000	640.778	0.359
OLC	1000	540.76	0.459

The cross-validated redundancy of the structural model is displayed in Table 8. The Q^2 values of the endogenous constructions are greater than 0. This demonstrated that the study model was extremely helpful for forecasting (Chin, 1998).

5.2.4 Hypothesis Testing

The PLS bootstrapping evaluation of a structural model is shown in Figure 3.

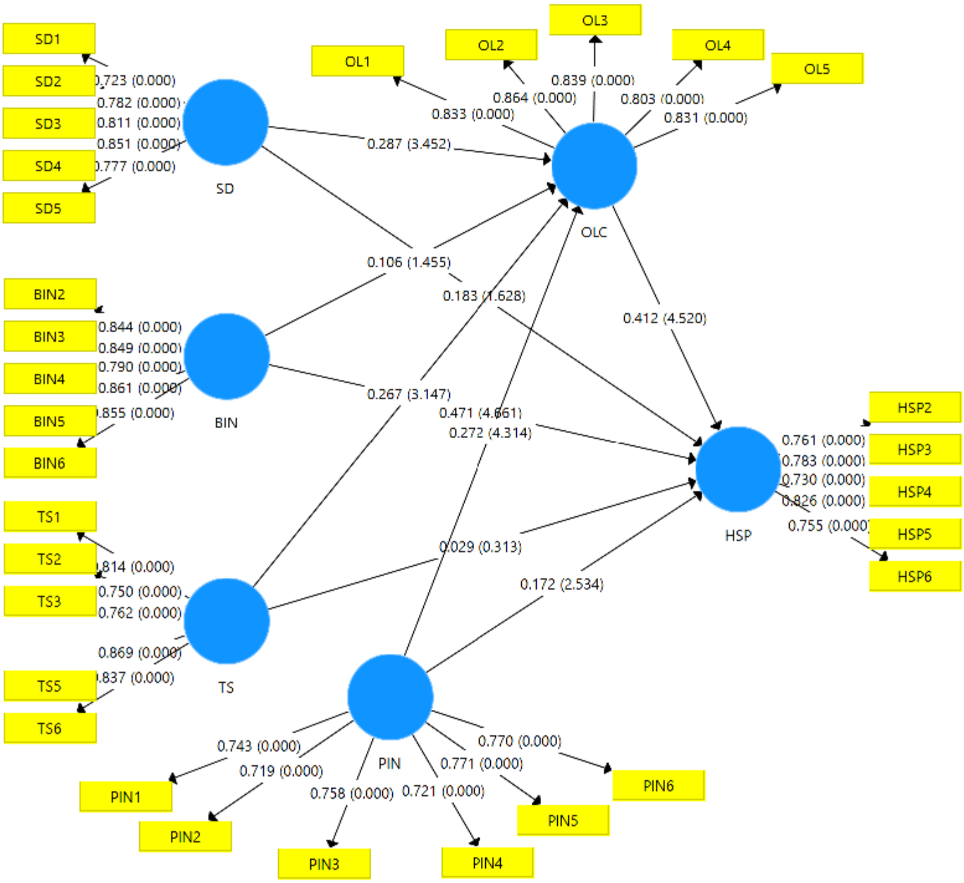

Fig. 3 - Assessment of structural model through PLS bootstrapping

Based on figure 3, the P-Values for the direct effects of system development, digital services, IT base innovations, and process integration on the dependent variable health service performance along with the direct effect hypothesis testing using t-values are shown in Table 9.

Table 9 - Results of bootstrapping (hypothesis testing)

Direct effect relationships	***PValues [p≤0.005]***	***Findings***
SD -> HSP	0.000	Supported
TS -> HSP	0.002	Supported
BIN -> HSP	0.000	Supported
PIN -> HSP	0.015	Not Supported

Four hypotheses are tested to determine whether safety digital service factors directly affect health service performance in the UAE. Below are the results of these hypotheses:

H_1: Organization system development has a significant impact on healthcare service performance.
The p-value is 0.000, so it is supported.
H_2: Technology services have a significant effect on healthcare service performance.
The p-value is 0.002, so it is supported.
H_3: IT-based innovation has a significant positive impact on healthcare service performance.
The p-value is 0.000, so it is supported.
H_4: Process integration has a significant effect on healthcare service performance.
The p-value is 0.015, so it is not supported.

Based on the results of the hypotheses, all the digital service factors have a significant effect on health service performance in the UAE.

In examining the role that organisational learning capacity as mediating the relationship between the dependent variable "digital service performance" and the independent variables of digital service innovation (system development, digital services, IT base innovations, and process integration), the results obtained form the PLS-SEM report are presented in table 10.

Table 10 - Indirect effect relationship

Indirect relationships	***PValues [p≤0.005]***	***Findings***
SD -> OLC -> HSP	0.002	Supported
TS -> OLC -> HSP	0.010	Not Supported
BIN -> OLC -> HSP	0.261	Not Supported
PIN -> OLC -> HSP	0.002	Supported

Examining the indirect impact of the mediator between the independent and dependent variables was obtained by testing four hypotheses as:

H_5: Organizational learning capacity has a positive mediating role between system development and healthcare service performance.
The result of the p-value is 0.002, so this hypothesis is supported.
H_6: Organizational learning capacity has a positive mediating role between technology services and healthcare service performance.
The result of the p-value is 0.010, so the hypothesis is not supported.
H_7: Organizational learning capacity has a positive mediating role between IT base innovations and healthcare service performance.
The result of the p-value is 0.261, so the hypothesis is supported.
H_8: Organizational learning capacity has a positive mediating role between process integration and healthcare service performance.
The result of the p-value is 0.002, so the hypothesis is supported.

Based on the findings of the indirect effect of organizational learning capacity as a mediator between the independent digital service factors and health service performance, it is clear that the mediator "OLC" has a high explanatory level that supports the role of the digital service innovations in enhancing the health service performance in the UAE. Table 11 displays the study's path coefficients.

Table 11 - Overall paths hypotheses

Hypothesis	**Relationship**	***PValues [p≤0.005]***	***Findings***
H1	SD -> HSP	0.000	Supported
H2	TS -> HSP	0.002	Supported

H3	BIN -> HSP	0.000	Supported
H4	PIN -> HSP	0.015	Not Supported
H5	SD -> OLC -> HSP	0.002	Supported
H6	TS -> OLC -> HSP	0.010	Not Supported
H7	BIN -> OLC -> HSP	0.261	Not Supported
H8	PIN -> OLC -> HSP	0.002	Supported

Table 11 shows the overall findings of the hypothesis from the model assessment.

5.2.5 Goodness-of-Fit (GoF) Assessment

Contrary to structural equation modelling based on covariance, PLS-SEM lacks a generally recognised global goodness of fit metric (Vinzi et al., 2010). This issue was addressed by Tenenhaus et al. (2004) with the "GoF" index, a global goodness of fit criterion. The index is composed of the average coefficient of determination and the geometric mean of the average communality (AVE) index (R^2). The following formula can be used to compute it.

$$GoF = \sqrt{\overline{AVE}\ X\ \overline{R^2}}$$

The GoF index concentrates on the model's overall prediction performance while attempting to explain the PLS model's performance at both the structural and measurement levels (Memon and Rahman, 2013). While the AVE addresses the quality of the index's measurement models, the R^2 in the formula stands for the structural model. A GoF index of 0.1, 0.25, or 0.36 indicates small, medium, or large, respectively (Akter et al., 2011). The following is the model's GoF index.

$$GoF = \sqrt{0.620\ x\ 0.610}$$

$$GoF = \sqrt{0.378}$$

$$GoF = 0.6148$$

The model's GoF is 0.6148 which is regarded as high, indicating that the research model is of high quality, according to Akter et al. (2011).

6. Conclusion

The major goal of this research is to investigate the digital service innovation that influences health service performance in the UAE. The study was accoplished through quantitative approach using questionnaire survey for data collection. The study examined a potential direct relationship between the performance of health services as the dependent variable and the four independent variables (system development, digital services, process integration, and IT base innovations). The results demonstrated that the performance of the UAE's health services is directly affected by the four independent variables. In all healthcare procedures and processes, technology is crucial (Tuckson, 2017). The results of this study are consistent with those of Zhamardiy et al. (2020), who claimed that healthcare services will become ineffective and patients will lose faith in them if new information technology is not regularly updated into them. Modern hospital innovations and technology have recently come under scrutiny for their effects on patient safety and the provision of safe care. To adapt and reduce errors in the provision of health services, significant changes in the environment and processes are needed (Chen et al., 2020). The study also examined the role of organisational learning capacity as mediator in health services. The results of the study confirmed that the organisational learning capacity is a mediator and has strong effect of health services. The findings of this study corroborate those of Khamis et al. (2014) who found that organisational learning capacity enhances the effectiveness of technology implementation. Organizations modify or revise their conceptual frameworks, rules, procedures, or competencies through the process of organisational learning in order to maintain or enhance performance (Chiva et al., 2014). Because this subject has not been thoroughly investigated in the context of the UAE, the research is anticipated to contribute to existing literature in terms of examining the digital service innovations related to health service performance in the UAE. The results showed a critical need for academics and researchers who are more focused on how developments in digital services impact the performance of health services. Additionally, the study identified areas where additional study is required to enhance the performance of health services, at least in relation to the UAE and other developing countries. This study will help academics better understand the nature of emerging digital service innovations and how to use them to improve the performance of health service.

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