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Health information technology and hospital performance the role of health information quality in teaching hospitals



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Main Naser Alolayyan^{a,*}, Mohammad S. Alyahya^a, Abdallah Hasan Alalawin^b, Aftab Shoukat^c, Farid T. Nusairat^a

^a Jordan University of Science and Technology, Faculty of Medicine, Health Management and Policy Department, Jordan

^b The Hashemite University, Faculty of Engineering, Industrial Engineering Department, Jordan

^c University of Engineering & Technology (UET) Pakistan, Institute of Business & Management, Pakistan

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ABSTRACT

The research purposed in this paper is to investigate the impact of the health information technology on hospital performance through the health information quality as mediating variable, as new evidence from the teaching hospitals in the north of Jordan. Research design and methodology approach based on a survey that is conducted to collect the requested data to develop a model connect between the health information technologies, health information quality and hospital performance by using the Structural Equation Modeling approach. The research findings show that there is an intertwined and reciprocal relation between Health Information Technologies (HITs), hospital performance, and health information quality. HITs have direct positive impacts on both hospital performance. Besides, health information quality functioned as a partial mediator between HITs and hospital performance and health information quality. This paper is evidence for the investor in the healthcare sector to invest more in HITs and health information quality, where the expected results are productivity improvement, performance leveraging and error reduction. The research or junction of this paper.

1. Introduction

Organizations think that they can combat competition by improving productivity, profitability, and quality of operations only if they invest in information technology and the information quality. The health care sector undergoes various changes as time passes and has achieved greater efficiencies and improved the consumer experience through the power of connectivity. Various researchers are agreed that more investment in Health Information Technology (HIT) and the quality of health information can decrease medical errors, reduces operational costs, and enhances the quality of health care processes, and adopting HIT could save billions of dollars, reduces drug events, and lead to a better doctorpatient relationship (Cantiello et al., 2016; El-Kareh et al., 2013; Kruse and Beane, 2018; Kruse et al., 2014; Norton et al., 2019; Singh and Sittig, 2016; Sittig et al., 2018; Wang et al., 2018; Zineldin et al., 2014).

Healthcare leaders view effective HIT as a remedy to meet the challenges of increased cost, medical errors, and service quality issues (Norton et al., 2019; Palvia et al., 2012; Waterson et al., 2013). In the health care process, there is a lot of literature on HIT pay off, but it overlooks the effect of actual IT usage on organization performance. This paper will discuss the impact of quality of health technology usage and health information quality on public teaching hospital performance. The expected result from this study will encourage the healthcare sector in Jordan and in developing countries to invest more in HIT and health information quality (Bawack and Kamdjoug, 2018; Hossain et al., 2019; Zayyad and Toycan, 2018).

2. Literature review

Information Technology (IT)'s business value has put a lot pressure on researchers into examining various approaches to understand the impact of IT in increasing organizational performance (Bipat et al., 2018; Brynjolfsson, 1993; Brynjolfsson and Yang, 1996; Dedrick et al., 2003; Fatafta et al., 2019; Hong and Wu, 2018; Hosseine et al., 2017; Turel

* Corresponding author. *E-mail address:* mnalolayyan@just.edu.jo (M.N. Alolayyan).

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et al., 2017; Wilson, 1995). Researchers used resource-based view theory to study the effect of a particular resource that an organization possesses to give a competitive advantage (Mata et al., 1995). Companies give credit for gaining a competitive advantage to IT after the priority of leadership (BolíVar-Ramos, GarcíA-Morales, & GarcíA-SáNchez, 2012; Sheng et al., 2013; Shukor et al., 2019). IT can streamline the processes, allowing the sharing and evaluation of patient information as a part of health information, and also gives patients access to care (Abomhara et al., 2018; Lee et al., 2013; McCullough et al., 2016). Health leaders are starting to appreciate IT usage in decreasing health care costs and improving service quality (Agha, 2014; Bardhan and Thouin, 2013; Kruse and Beane, 2018; Okpala, 2018; Turan and Palvia, 2014; Wang et al., 2018). The use of HIT increased productivity, competitiveness, and quality (Feeley et al., 2020; Miraldo et al., 2019; Remondino, 2018; Risko et al., 2014; Rutten et al., 2014).

Corresponding to El-Kareh et al. (2013) and Walsham (2012), many healthcare providers consider HIT as a solution to medical errors. In the banking and aviation industry, human errors are reduced through effective use of IT (Turan and Palvia, 2014), and, in the same way, medical errors are reduced using HIT (Balicer and Cohen-Stavi, 2020; El-Kareh et al., 2013; Rodziewicz and Hipskind, 2019). If there is electronic access available to complete a patient's health information, it will reduce medical errors that occur because of gaps in knowledge about issues like allergies, relevant medication and laboratory information, past medical history, and poor communication among providers (Risko et al., 2014; Rodziewicz and Hipskind, 2019; Wears, 2015).

Health Information Technology (HIT) systems, like automated decision making and knowledge acquisition support tools, can bring electronic patient information (health information) that can be effectively used by health care practitioners, thereby reducing errors of omission due to gaps in provider's knowledge and failure to use that knowledge in health care practice. HIT also improves queue management, saves a lot of stationary costs, reduces various barriers, and employees are relieved of various paper related jobs (Ibanez et al., 2018; Jones et al., 2012; Kuo, 2018; Limanto and Andre, 2019; Rezaee and Pasandideh, 2018; Weiss and Tucker, 2018). Also, according to Bardhan and Thouin (2013), the use of a financial management system has a direct effect on reducing hospital operating expenses. Lee et al. (2013) were of the view that HIT can help in the delivery of health care services efficiently and effectively. Devaraj, Ow, and Kohli (2013) used the theory of swift and even flow to study the role of IT on patient flow and its effects on hospital efficiency and performance. They found that IT has a positive relationship with swift and even patient flow, achieving an increased revenue for hospitals. The result also showed that financial performance increased without disturbing quality. Swift flow affects the financial performance of the hospital, while even flow has an impact on quality. Both reinforce each other to increase hospital performance. From another view, according to (Ferretti et al., 2019), studying of using IT in health care is important for various countries, as it helps in learning, but a comparison study is difficult to conduct for IT in health care across countries, as various terminologies are used. To eliminate the problem, the Organization for Economic Corporation and Development (OECD) launched a benchmarking ICT in health system project, which is a multi-participatory initiative to make sure that quality data is available and indicators for ICT in health. Many researchers focused on the impact of HIT on one or more of the hospital performance characteristics, some of these studies are conducted in developed countries, and some others are conducted in developing countries, but still developing countries need more investigation in this filed (Amarasingham et al., 2009; Bello et al., 2004; Carayon et al., 2020; Gyamfi et al., 2017; Handayani et al., 2013; Liao and Lin, 2020; Raptis et al., 2009).

The quality of health information depends on the quality of the primary data. To implement effective decision-making, whether at the clinical or strategic level of health care, you need a high quality of health information. In one study, 42 percent of interviews that identified poor data quality in healthcare were considered a major hindrance in decisionmaking (Foshay and Kuziemsky, 2014). The same study stated that there are large efforts and cumbersome processes in health care to request and document health information, there are no specific standards and measures for the quality of information, and therefore lack of understanding of information needs, and ways to obtain value from data, often need manual work related to the privacy of health information.

3. Theoretical framework

Scientific management theory is the first management theory after the industrial revolution. It aims to scientifically determine the best method to perform the tasks by the efficient allocation of human and nonhuman resources to increase productivity and eliminate waste (focus on operations), Established by Fredrick Winslow Taylor (1856–1915), Father of Scientific Management-an American mechanical engineer, so our research depends on the Scientific management theory and the Fayol's 14 principles of management to build the relationship between Quality of Health Information Technology and Hospital Performance.

Plantier et al. (2017) researched in French hospitals regarding how Electronic Medical Record (EMR) affects health care quality. Quality of care management was measured in this research by using four indicators: namely the patient data quality, pain status, nutritional status evaluation, and transmitting information delay. The electronic medical record was evaluated in comparison with paper health records by keeping the type of hospital (teaching, public, private, not for profit, and for-profit), the number of beds (size), and the region as control variables. These results showed that total or partial use of EMR has a positive effect on the quality of care management.

Devaraj and Kohli (2000) examined longitudinally the impact of IT on the hospital's performance across the United States, which recently adopted a Decision support system (DSS). DSS is a computer system that helps to increase the effectiveness and productivity of the manager. It helps to make decisions regarding strategic, operational and managerial issues. Operational decisions are decisions made at patient care level; Managerial cutting and overall profitability of a department etc. Strategic decisions involve contracting, pricing decisions involve cost-and merger and acquisition decisions. The findings of this research revealed that there is increased profitability within three months. They also examined the effect of IT on Business Process Reengineering (BPR) and found that BPR initiatives in those hospitals realized after two years because of the use of IT.

Mapesa (2016) studied the effects of HIT on the performance of hospitals and found that the use of IT affects hospital performance in terms of enhanced productivity, increased profitability, and improved quality. Williams, Asi, Raffenaud, Bagwell, and Zeini (2016) did research on the effects of the use of IT in 1,039 hospitals in the United States and found that by giving electronic access to diagnostic results of a test like cardiac imaging, nuclear test, blood test, and radiological exam, hospitals can provide quality health care to their patients.

The researchers are proposing the following hypothesis:

H1. Health information technology has a positive impact on hospital performance

Mohammed and Yusof (2013) studied the information quality in health information systems. They selected six frameworks from health informatics and information systems literature to identify the criteria from a human perspective. They recommended more attention on the information quality from the technology side and from the organization performance side. Kilsdonk, Peute, and Jaspers (2017) showed clear gaps in research on organizational factors associated with a successful implementation of IT, they recognized a gap in the implementation of Information Quality and System Quality to facilitate clinical decision support systems. Considering the above discussion and previous studies, Several studies have shown the effect of information quality on organizational performance through several organizational factors. These factors include service integration, user needs, human resources, and communications (Alenezi et al., 2015), quality improvement (Fotopoulos and Psomas, 2010), customer satisfaction of information system (Daunoriene and Zekeviciene, 2015). The researchers are proposing the following hypothesis:

H2. Quality of health Information has a positive impact on hospital performance

Today, electronic medical records are the largest source of health information, and thus the quality of health information technology has an important impact on the ease and quality of using electronic medical records systems in addition to privacy, safety, and speed. However, research studies are limited in linking the quality of health information technology to the quality of health information. There are no comprehensive studies to determine the values or contributions of errors related to the quality of documentation processes or the quality of health information in the electronic record, e-health and negative clinical events resulting from the information quality of electronic medical record. Also there is as yet no agreement on what "health data quality" means in the context of records e-health (Weiskopf and Weng, 2013). Some defective functions in health information technology can mislead the doctors, for example, the presence of a confusing display, problems in the health information system such as input or output the data and health information, defective in saving the heath information and defective when producing incorrect values for example (pounds to kilograms or Celsius to Fahrenheit). All of these things and more affect the treatment process and the medical doctor's decisions and medical staff behavior (Phillips and Fleming, 2009). The researchers are proposing the following hypothesis:

H3. Health information technology has a positive impact on health information quality

By building the previous hypotheses that showed that there is a positive relationship between health information technology and hospital performance, as well as there is a positive relationship between health information technology and the quality of health information, there is also a positive relationship between the quality of health information and the hospital performance. Researchers here based on the above assume that, there is a positive relationship between health information technology and hospital performance through the quality of health information as an mediating variable.

H4. There is an indirect impact of health information technology on hospital performance through health information quality (Figure 1).

4. Methodology

4.1. Research methodology

In this section, the sample and data collection procedure used in this study are discussed. Additionally, a detailed description of the operational measure of variables and the statistical evaluation of hypotheses is given. Based on previous sections, a conceptual framework and research instrument has been developed. The following section will describe the collection of data and measurement of variables procedures for the constructs.



Figure 1. Research model.

4.2. Papulation of the study, data collection and measurement scale

The data collection was done through a questionnaire. A face to face set of data was collected manually for most responses. Data collection was done by questions related to the health information technology, health information quality and hospital performance. The data were collected from the clinical leadership, medical staff supervisors, management supervisors and medical doctors (most people used the information technology tools and quality of health information) related to different departments in public teaching hospitals in the north of Jordan. The respondents belong to all hospital departments and include all types of medical doctors (MD) (specialist and resident). The population size of the five hospitals was assessed through interviews with human resources management specialists in five hospitals. The size of the population was approximately 1,500 between physicians, medical department heads, non-medical department head, and medical and nonmedical supervisors. The respondent rate was around 90 percent from five different teaching hospitals in the north of Jordan. Total sample size is 480 questionnaires that have been considered, as 53 Out of 533 distributed forms were excluded. This sample size of the collected questionnaires was sufficient for research hypotheses testing (J. F. Hair, Black, Babin and Anderson, 2013). Hospital participation is presented in Table 1.

4.3. Sampling methods

Careful consideration should be taken to decide the adequate sample size in order to achieve an accurate result (Creswell, 2008). suggests choosing as large a sample as possible to have a lower chance to differ from the considered population. A smaller sample may extract an inaccurate research conclusion. The best sample size, however, differs upon the research type, but generally, for each independent variable, five observations are recommended by (Hair et al., 2013). When the data follows the normal distribution, five observations per independent variable is suggested by Bentler and Chou (1987) when latent variables have multiple indicators.

Generally, the accepted number for the sample size is ten observations per indicator variable (Nunnally, 1994) To satisfy the above condition, the scholars carefully chose a suitable sample size of 480 respondents for 41 observations in the study instrument from the participating hospitals. A stratified random sampling method was used to select respondents from the observed population. From 480 respondents, the female and male percentages were 61.5 and 38.5 percent, respectively. Their ages ranged from 20 to 80, and they were categorized into four groups, with each group having a 15-year range and a 46.0, 40.6, 11.7, and 1.7 percent response rate, respectively. The sample profession frequency and percentage of it are shown in Table 2.

Regarding their professions, 5.6 percent of respondents were managers, 38.5 percent were senior officers and supervisory-level management, 20.65 percent of respondents were head of department and head of medical units, and 35.25 percent of respondents were resident doctors and specialist doctors. From the respondents' group, 14.4 percent of belonging to less than 2 years, 20.4 percent of respondents belong to 2–5 years, 22.9 percent of respondents belong to 5–10 years, and 42.3 percent of respondents belong to 10–25 years. Their education level is summarized in Table (3).

4.4. Variable measurement

Testing of hypotheses is done by using Analysis of Moment Structures (AMOS) and Structural Equation Modeling (SEM) software that are available in Statistical Package for the Social Sciences (SPSS) version 22, AMOS version 22. In this research, the measure of reliability was done by using Cronbach's alpha. Exploratory Factor Analysis was also performed to discover the interaction between studied variables. Additionally, a second-order Confirmatory Factor Analysis was employed to verify that

Table 1. Hospital names and Hospital participation percent.

Name of the hospital	Frequency	Percent (%)
Princess Basma Hospital	132	27.5
King Abdullah University Hospital	124	25.8
Princess Badea'a Hospital	72	15.0
Princess Rahma Hospital	111	23.1
Gynecology and Pediatrics' Hospital—Almafraq	41	8.5
Total	480	100.0

Table 2. Sample of Professions, frequency and percentage.

Professions	Frequency	Percent (%)
Manager	27	5.6
Senior officer	123	25.65
Head of department	59	12.3
Supervisors	62	12.9
Head of Medical Unit	40	8.35
Resident Doctor	110	22.9
Specialist Doctor	59	12.3
Total	480	100.0

Table 3. Education level, frequency and percentage.

	Frequency	Percent
Diploma	73	15.2
Graduate degree	170	35.4
Postgraduate	144	30.0
Higher Specialty in Medicine	93	19.4
Total	480	100.0

the hypothesized construct in research loads into a specific number of underlying sub-constructs or components and, in addition, to test the construct validity. In the final stage, we used the Structural Equation Modelling (full-fledged measurement model, and full-fledged structural model) to determine the impact between independent, mediating and dependent variables.

Three-elements of health information technology were captured by a total of 14 items, namely interface, functions, and performance. The 14 items were divided into eight items for the screen interface—three items for functions reversibility and three items for performance integration of systems. A seven-point Likert scale was used to measure all items from -3 to 3 (Ribière et al., 1999).

The mediating variable (health information quality) was captured in 8 items in one dimension. A seven-point Likert scale was used to measure all items from -3 to 3, the dimension covering the following areas (Accurate, Complete, Current, Sufficient, Understandable, Secure (ensure confidentiality), Uniformly defined (standardized), and Timely (available as it has been collected)) (Ribire et al., 1999).

For hospital performance, there were six dependent variables captured by a total of 27 items, namely process orientation, clinical quality, workforce conditions, patient satisfaction, operational efficiency and financial performance. The 27 items were divided into nine items for process orientation, three items for workforce conditions, four items for clinical quality, four items for patient satisfaction, four items for operational efficiency, and three items for financial performance (Chen et al., 2009; Griffith et al., 2006; Griffith et al., 2002; Gumbus et al., 2003; Kershaw and Kershaw, 2001; Lovaglio, 2011; Meyer and Collier, 2001; Vera and Kuntz, 2007; Walker and Dunn, 2006; Zelman et al., 2003). A Five-item Likert scale was developed to assess the 27 items, where

strongly disagree was represented by 1 and strongly agree was represented by 5.

5. Statistical analysis and results

5.1. Reliability

Reliable measurement instrument should be able to reproduce a specific study's outcome using a similar methodology, that is, give a replicable, repeatable, and stable measurements overtime (Golafshani, 2003; Kirk et al., 1986). For this study, the reliability scores of the constructs are presented in Table 4.

A strong significance can be concluded from the reliability scores shown in Table 4. For the health information technology dimensions, the interface dimension was 0.950, function was 0.887, and performance was 0.895, also for health information quality dimension was 0.953, while the overall health information technology dimensions, hospital performance constructs, and health information quality were 0.949, 0.934, and 0.953, respectively. The Cronbach's alpha scores ranged from 0.681 to 0.95, therefore, confirming items' internal consistency for all considered dimensions (Nunnally, 1994).

5.2. The exploratory factor analysis

After data entry, a rigorous exploratory factor analysis (EFA) was implemented to distinguish the underlying dimensions. This was done by applying a principle Components Extraction Method with promax rotation, taking into consideration all the items adapted for health information technology dimensions, hospital performance dimensions,

Table 4. Reliability test.

Dimensions Code	Dimensions	Number of items	Cronbach's Alpha
QIT Interface	Interface	8	0.950
QIT Function	Function	3	0.887
QIT Performance	Performance	3	0.895
HP_POI	Process orientation	9	0.890
HP_WC	Workforce conditions	3	0.681
HP_CQ	Clinical quality	4	0.776
HP_P	Patient satisfaction	4	0.809
HP_OE	Operational efficiency	4	0.805
HP_FP	Financial performance	3	0.749
Over all dimensions Health Information Technology		14	0.949
Over all items Health Information Quality		8	0.953
Over all dimensions Hospital Performance		27	0.934

Table 5. Representing EFA pattern matrix^a for Health Information Technology.

	Component		
	1	2	3
QIT- Interface 6	0.889		
QIT- Interface 1	0.872		
QIT- Interface 3	0.868		
QIT- Interface 2	0.838		
QIT- Interface 7	0.832		
QIT- Interface 4	0.805		
QIT- Interface 8	0.794		
QIT- Interface 5	0.790		
QIT- Performance 2		0.934	
QIT- Performance 1		0.876	
QIT- Performance 3		0.839	
QIT- Functions 1			-0.870
QIT- Functions 3			-0.849
QIT- Functions 2			-0.837
^a Rotation converged in 9 iterations			

Table 6. Representing KMO and Bartlett's test.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.935
Bartlett's Test of Sphericity	Approx. Chi-Square	5,906.837
	Df	91
	Sig.	0.000

and health information quality. With eigenvalues more than 1, Kaiser's rule principle was applied with a more easily interpretable factor loading to verify the dimensions to retain health information technology (Pallant and Manual, 2007). EFA results presented in Table 5 shows the dimensional nature of the constructs. Health information technology has three components: Interface (eight items); Performance had (three items), and Functions had (three items). EFA outcomes for each construct for Health Information is presented in Tables 5, 6, and 7.

EFA findings presented in Table 8 shows the unidimensional nature of the constructs. Hospital performance has five components: process orientation (nine items); workforce conditions (three items); clinical quality (four items); patient satisfaction (0 items); operational efficiency

(four items), and financial performance (two items). EFA outcomes for each construct for hospital performance are presented in Tables 8, 9, and 10.

5.3. Confirmatory factor analysis (CFA): validity and reliability

In this research, the confirmatory factor analysis (CFA) procedures of validation that were recommended by Byrne (2013) and Kline (2015) were followed. Construct validity was assessed by a second order confirmatory factor model by employing the maximum likelihood method. This model was applied to health information technology, health information quality and hospital performance constructs. The results are shown in Table 11. However, the sensitivity of this model to

Table 7. Representing total variance explained.

Component	Initial Eigenvalues		Rotation sums of squared loadings	
	Total	% of Variance	Cumulative %	Total
1	8.444	60.315	60.315	7.681
2	1.491	10.653	70.968	5.432
3	0.989	7.062	78.030	5.302
4	0.583	4.164	82.194	
5	0.404	2.887	85.081	

Table 8. Representing EFA Pattern Matrix^a for hospital performance.

1 HP-OE_3 0.79 HP-OE_2 0.70 HP-OE_4 0.67 HP-OE_1 0.56 HP-P.3 0.49 HP-P-3 0.49 HP-P-2 0.45 HP-01-2 1 H-PO1-3 1 H-PO1-5 1 H-PO1-8 1	2 93 09 76 55	3	4	5	_
HP-OE_3 0.799 HP-OE_2 0.700 HP-OE_4 0.674 HP-OE_1 0.566 HP-P-3 0.499 HP-P-4 0.488 HP-P-2 0.456 H-POI-2 H-POI-3 H-POI-5 H-POI-6 H-POI-7 H-POI-7	93 09 76 65				
HP-OE_2 0.70° HP-OE_4 0.67° HP-OE_1 0.56° HP-P-3 0.49° HP-P-4 0.48° HP-P-2 0.45° H-POI-2	09 76 65				
HP-OE_4 0.67/ HP-OE_1 0.56/ HP-P-3 0.49 HP-P-4 0.48 HP-P-2 0.45' H-POI-2 1 H-POI-5 1 H-POI-6 1 H-POI-7 1	76 65				
HP-OE_1 0.566 HP-P-3 0.499 HP-P-4 0.488 HP-P-2 0.457 H-POI-2 H-POI-3 H-POI-5 H-POI-6 H-POI-8 H-POI-7	65				
HP-P-3 0.49 HP-P-4 0.48 HP-P-2 0.45 H-P0I-2 H-P0I-3 H-P0I-5 H-P0I-6 H-P0I-8 H-P0I-7	20				
HP-P-4 0.48 HP-P-2 0.45 H-POI-2 H-POI-3 H-POI-5 H-POI-6 H-POI-8 H-POI-7	90				
HP-P-2 0.45 H-POI-2 H-POI-3 H-POI-5 H-POI-6 H-POI-8 H-POI-7	88				
H-POI-2 H-POI-3 H-POI-5 H-POI-6 H-POI-8 H-POI-7	59	0.4	146		
H-POI-3 H-POI-5 H-POI-6 H-POI-8 H-POI-7	-0.7	63			
H-POI-5 H-POI-6 H-POI-8 H-POI-7	-0.7	'49			
H-POI-6 H-POI-8 H-POI-7	-0.7	22			
H-POI-8 H-POI-7	-0.7	/10			
H-POI-7	-0.7	'06			
	-0.7	02			
H-POI-4	-0.6	84			
H-POI-9	-0.6	51			
H-POI-1	-0.5	98			
HP-CQ1		0.7	746		
HP-CQ3		0.6	589		
HP-CQ2		0.6	580		
HP-CQ4		0.6	507		
HP-P-1		0.5	565		
HP-FP-2			0.	677	
HP-FP-3			0.	668	
HP-FP-1					
HP-WC-1				0.6	593
HP-WC-2				0.6	531
HP-WC-3				0.4	484

Table 9. Representing KMO and Bartlett's test.		
KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.925
Bartlett's Test of Sphericity	Approx. Chi-Square	6,188.095
	Df	351
	Sig.	0.000

the sample size was worth mentioning, and therefore, several cases per free parameter should be taken into consideration.

All second order CFA results are statistically accepted and the goodness of fit indices of the models are stated in the acceptable ranges and support the adequacy of the models based on goodness of fit statistics that conform to the recommended values (Hair et al., 2013). To verify the validity and reliability of the study instruments, both the composite reliability (CR) and average variance extracted (AVE) were used. The CRs were over the threshold of 0.70 and the AVEs of all measures were greater than 0.5, as reported in Table 12. This shows a convergent validity of the constructs. Moreover, the loading factor for all items was above 0.58 or a p-value of less than 0.05 (Kline, 2015).

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Table 10. Representing total variance explained.

Component	Initial Eigenvalues			Rotation sums of squared loadings
	Total	% of Variance	Cumulative %	Total
1	10.098	37.402	37.402	10.098
2	2.060	7.631	45.032	2.060
3	1.389	5.144	50.176	1.389
4	1.310	4.852	55.028	1.310
5	1.040	3.852	58.880	1.040
6	1.013	3.751	62.631	
7	0.872	3.228	65.859	

EFA findings presented in Table 11 shows the unidimensional nature of the constructs. Health information quality has one component (four items); EFA outcomes for each construct for hospital performance is presented in Tables 11, 12, and 13.

Table 11. Representing EFA Pattern Matrix^a for health information quality.

	Component	
	1	2
HIQ7	.957	
HIQ6	.941	
HIQ8	.813	
HIQ5	.772	
HIQ4	.504	456
HIQ1		-1.008
HIQ2		890
HIQ3		678
^a Rotation converged in 7 iterations.		

Table 12. Representing KMO and Bartlett's test.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.939
Bartlett's Test of Sphericity	Approx. Chi-Square	3694.507
	Df	28
	Sig.	.000

Therefore, all the selected items were significant to measure the study variables following the rule of (Hair et al., 2013). A confirmatory factor analysis was conducted to assess the model. The findings showed that the data fit the model well: $\chi^2/df = 3.537$; comparative fit index (CFI) = 0.901; root mean square error of approximation (RMSEA) = 0.073 and GFI = 0.876, p. value (>0.05) = 0.000 (Kline, 2015).

5.4. Full-fledged SEM analysis

The direct and indirect impacts between constructs is studied in this section. At first, a full-fledged structural equation modelling (SEM) analysis was conducted, as quantitative research scholars suggested that, this analysis can observe and discover the effect between constructs adequately (Byrne, 2013; Kline, 2015). Although the performed SEM model indicated that data can be described accurately using the hypothesized model, some crucial deductions were revealed. First, health information technology has direct positive impact on hospital performance ($\beta = 0.32$; p < 0.000); health information technology has direct positive impact on health information quality ($\beta = 0.79$; p < 0.000), health information quality has direct impact on hospital performance (β = 0.40; p < 0.000) all β < 0.2. In other side, health information quality plays a partial mediating role between health information technology and hospital performance (β = 0.316; p < 0.000, β < 0.08 (Byrne, 2013), Figure 2 and Table 13 provided clear proof of the 'goodness of fit' of the model. In Figure 2, the three factors of the health information technology

(interface, function, and performance) are represented in the SEM model, health information quality construct is represented, and the Hospital Performance constructs are also represented in the SEM model.

The estimated causal impact of constructs of the full-fledged SEM model are shown in Figure 2. The model contains a total of 40 items for the eight constructs (14 items for health information technology, 4 items for health information quality and 22 items for hospital performance). The model provided adequate good fit for the study data. The goodness of fit statistics summary of the model is demonstrated in Table 13. The root mean square error of approximation (RMSEA), the comparative fit indices (CFI), and other goodness of fit indices of the model are stated in the acceptable ranges and support the adequacy of the model based on goodness of fit statistics that conform to the recommended values. The statistics ranges, which were used, were RMSEA <0.08, CFI >0.9, and normed chi-square < 5 (Bollen, 1989; Byrne, 2013; NE & Cudeck, 1993).



Figure 2. Full-fledged structural equation model.

Table 13. Representing total variance explained.										
Component	Initial Eigenvalues	Rotation Sums of Squared Loadings								
	Total	% of Variance	Cumulative %	Total						
1	6.045	75.564	75.564	5.618						
2	.524	6.553	82.116	5.271						
3	.370	4.631	86.747							

Additionally, loading coefficients ranged between 0.76 – 0.95 without any offending estimates sounds reasonable and is far greater than the 0.5 threshold recommended by (Byrne, 2010). Further examination of the estimated outputs supports the statistically significant relationships among all constructs. Clearly, the relationships among process orientation (nine items), workforce conditions (three items), clinical quality (four items), operational efficiency (four items), and financial performance (two items) are considered statistically significant. This can be noted by the absolute critical ratio (CR) values that are greater than 1.96 (alpha level of 0.05) for the inter-variable relationships (Byrne, 2013). Also, the model revealed that there were no direct and indirect relationships among the constructs of the model. All effect estimates were statistically significant and logically reasonable, and their values are of an acceptable standard for evidence of direct effects (Byrne, 2013).

Figure 2 and Table 14 show a causal impact of health information technology on hospital performance, the impact of health information technology on health information quality, impact of health information quality on hospital performance, and indirect impact of health information quality as a partial mediating role., Also, the results of path analysis between all the three variables are high compared with 0.2, and the indirect results higher than compared 0.08 (J. Hair, Black, Babin, Anderson and Tatham, 2010) (see Tables 15, 16, 17).

6. General discussion

In this study, six different indicators were used as hospital performance measures to test our hypothesized model. These indicators include financial performance, clinical quality, process orientation, workforce conditions, operational efficiency, and patient satisfaction, later was excluded from the exploratory factor analysis results. Our proposed model shows that there is an intertwined and reciprocal relation between HITs, hospital performance, and health information quality. The exploratory factor and confirmatory factor analyses show that the three main constructs of HITs (interface, function, and performance) and health information quality construct are valid in testing hospital performance indicators. Furthermore, the full-fledged structural equation modelling (SEM) and the causal effects among the constructs analyses consistently revealed that HITs have direct positive impacts on both hospital performance and health information quality. Health information quality has also a direct impact on hospital performance. However, health information quality plays a partial mediating role between HITs and hospital performance. This means there is an indirect impact of HIT on hospital performance through health information quality as a partial mediator.

Specifically, we found that HITs had a statistically significant impact on better clinical quality. Consistent with this result, a positive link was found between hospital implementation of HITs and practices and strategies that intend to improve clinical quality with higher hospital performance and medical outcomes (Kruse and Beane, 2018; Restuccia et al., 2012). HITs are considered enablers of clinical quality practices and quality improvement strategies through performance monitoring, enhanced documentation, information transfer and communication, and medical errors prevention, thus leading to higher quality performance and efficiency (Restuccia et al., 2012). Bojja and Liu (2019) analyzed longitudinal data from over 400 US hospitals that included IT budgets and financial and non-financial hospital performance measures. They used mortality as a measure of healthcare quality and concluded that HIT budgets are of vital importance for health care quality in hospitals.

However, other studies argued that more hospital technology does not necessarily lead to improving all quality measures of patient care (Williams et al., 2016). Parente and McCullough (2009) examined the association between three HITs (electronic medical records (EMRs), nurse charts, and picture archiving and communications systems (PACS) and three patient safety indicators (postoperative hemorrhage or hematoma, infection due to medical care, and pulmonary embolism or deep vein thrombosis). The only statistically significant relationship found was between EMRs and reduced infections due to medical care. Similarly, Daniel (2018) found that hospitals with the highest HIT scores for certain measures showed modest and statistically significant reduction in 30-day readmissions, with no improvement in length of stay.

In terms of financial performance, our results are in line with previous studies that show a significant positive effect of HIT investment on hospitals financial revenues, income or cash flow, and operational efficiency (Lee and Choi, 2016, 2019; Menachemi and Brooks, 2006; Menachemi et al., 2006). In their economic evaluation meta-analysis of HIT, Bassi and Lau (2013) found that about 70% of studies reported value for invested money on HITs. HITs can increase hospital revenues in several ways, including reductions in length of stay, medical errors, unnecessary tests, uncompensated care, and administrative expenses. HITs can also increase the efficiency of tracking and following-up insurance coverage, bad debts, and billings (Garrido et al., 2004; Girosi et al., 2005; Lee and Choi, 2019). Oh, Zheng, and Bardhan (2018) studied the role of IT in hospital operational efficiency based on the deviation between hospital length of stay and the geometric mean LOS (GMLOS) guidelines; they found that implementation of HIT applications for operational coordination of patient care increases hospitals' adherence capabilities related to standard guidelines on length of stay Thus, it can be argued that HIT can enhance hospital operational efficiency.

While the impact of HITs on the financial performance and quality of healthcare delivery has been extensively studied (Brenner et al., 2016;

Гаb	le	14.	Summary	of	fit	statistic	inc	lexes	for	the second	l orc	ler C	lonf	firmatory	7 Factor	Analy	ysis	mod	el.
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Models	X ²	Df	Р	C _{mindf}	RMSEA	CFI	TLI	GFI	P/estimates
Health Information Technology	203.907	71	0.000	2.872	0.063	0.977	0.971	0.942	(0.71–0. 89)
Health information Quality	57.5	18	0.001	3.194	0.074	0.921	0.917	0.895	(0.74–0.81)
Hospital performance	606.861	202	0.000	3.004	0.065	0.911	0.898	0.894	(0.58–0.83)

Note: N.B: all loadings were statistically significant at an alpha level of p = 0.05.

Table 15. Average variance extracted (AVEs) and composite reliability (CRs).

		Avera	ge Variance Extr	Composite	Composite Reliability (CRs)			
Health Information Technology	0.696					0.967		
Health Information Quality		0.717					0.878	
Hospital Performance		0.514					0.93	
Table 16. Fit statistics for the full-fledged	l SEM model.							
Models	X ²	Df	Р	Cmindf	RMSEA	CFI	GFI	P/estimates
	2560.944	724	0.000	3.537	0.073	0.901	0.876	(0.76-0.95)
Fit statistics for QHIT, HIQ and HP Model	2500.844	/=.						(01/0 01/0)

Rahurkar et al., 2015), few studies have examined the role of the HITs on hospitals' process orientation and work conditions. Our results revealed that HITs have a potential positive impact that enhances process orientation and improves hospital work conditions. In line with this, Radhakrishnan et al. (2008) studied over 80 firms and provided strong empirical evidence that organizations that focus on IT and take measures to effectively absorb, diffuse, manage, and employ IT at the process level create higher process capabilities and enjoy a differential business value along process-oriented dimensions. Regarding work condition improvement, it has recently been found that HITs can improve workflow in healthcare settings by sharing information, facilitating task organization, and supporting timely communication between the interdisciplinary care team (Haque et al., 2019).

Our model also showed that HITs has a direct positive effect on health information quality, and health information quality has a direct effect on hospital performance. Besides, health information quality functioned as a partial mediator between HITs and hospital performance. The quality of health information was evaluated by the accuracy, completeness, up-todate, sufficiency, understandability, secureness, standardized, and availability. Previous studies found that health information quality in HITs plays a key role in managing, planning, and providing useful knowledge for both managers and health care providers. However, low quality of information could cause numerous performance problems such as increase medical errors, high cost, and low quality of care (Byrd and Byrd, 2013; Cabitza and Batini, 2016; Mohammed and Yusof, 2013). Nonetheless, timely access to accurate, complete and up-to-date health information is crucial in providing tailored, contextualized, and effective healthcare to patients (Bouamrane et al., 2012; Cabitza and Batini, 2016). The availability of such health information supports decision making for healthcare providers. It helps in clarifying and verifying information used in patients' diagnosis and treatment planning. HITs improve the quality of health information by utilizing a standard coding and endorsing it in electronic records. This facilitates data sharing and exchange of health information between hospitals' departments, units and health care providers (Hovenga et al., 2010).

On the other hand, functions offered by HITs such as clinical decision support systems, exchange of information, and knowledge management support planning, coordination, and integration activities and streamlining of workflows in the hospitals. However, efficient HITs functions are critically dependent on the quality of retrieved information (Bouamrane et al., 2012; Kilsdonk et al., 2017). Thus, high quality health information is an enabler for better organizational and patients' outcomes.

7. Managerial implications

With increased investment in HITs in recent years by healthcare settings in low- and middle-income countries, the results of the current study are of great benefit for clinicians and administrative staff to leverage their knowledge about the impact of HITs. This study delivers a thoughtful perspective for understanding how HITs can significantly and positively impact both hospital performance and health information quality.

Hospitals are composed of wide and heterogeneous units and services and have considered as complex systems. Such systems are information centric. This study justifies the importance of investments in IT technologies that can improve work conditions and process orientation in hospitals, through increasing team coordination and collaboration, simplifying daily clinical and administrative tasks, and reducing work redundancy. Furthermore, deployment of HITs will continue to have an impact on improving communication links with and within different hospital departments and allowing healthcare professional and administrative staff to work remotely.

Additionally, efficient HITs provide hospital units with accurate and timely information that required to meet dynamic patient needs and provide a quality care for patients. HITs help health care managers and healthcare providers in managing health information efficiently, especially with high volume and variety of health data and information. For instance, data mining, and text mining have become integrated parts of the health information systems. These new solutions which are highly dependent on health information quality play a critical role in extracting new knowledge, quantifying the impacts of healthcare interventions, reducing medical errors, and guiding evidence-based practices, either clinical or nonclinical practices (Islam et al., 2018; Kudyba, 2018; Yadav

Table 17. Analysis of causal effects among the constructs.											
Dependent variable		Impact	Independe	nt variable	Results of direct impact (β)						
Hospital performance		<	Health inf	ormation technology	0.32***						
Health Information Quality		<	Health inf	ormation technology	0.79***						
Hospital performance		<	Health Inf	ormation Quality	0.4***						
Indirect impact											
Dependent variable	Impact	Mediating variable	Impact	Independent variable	Results of in- direct impact (β)						
Hospital performance	<	Health Information Quality	<—	Health information technology	0.316						

et al., 2018). Consequently, the utilization of HITs has the potential to improve patient care and enhance intra-organizational communication.

8. Conclusion

Based on the validation results of the impact of the HITs model, the model can be considered sufficiently valid to be used in the hospitals to study their performance measures. Our model confirms a significant positive effect of the quality of HITs on hospital performance and health information. Health information quality is a key input of the quality of clinical and administrative decisions and practices. Interestingly, this study found that HITs have an indirect impact on hospital performance through health information quality, as a mediator. HITs have been shown to improve performance in hospital settings. Finally, while ample empirical research has tried to study if HITs bring out clinical and nonclinical benefits to healthcare facilities, not much attention has been paid to studying the impact of HITs on work conditions and process orientation. We hope that the valid measurement tool used in this study sets a stage for further research on the role of HITs in improving the work conditions and business process orientation, especially in complex work environments (i.e., hospitals).

9. Limitations and future research

This study was based on a quantitate research approach. Further research including qualitative (i.e. interviews and observational) studies would allow for triangulation of data, which could enhance the generalizability of the results and verify our model. The study did not examine the factors that influence the relationship between HITs, hospital performance and health information quality. Future research future researchers must focus more on the relationship between HITs and how it might impact the quality of health information, clinical decision making, and organizational performance.

Declarations

Author contribution statement

Main Naser Alolayyan, Mohammad S. Alyahya: Conceived and designed the experiments.

Abdallah Hasan Alalawin: Analyzed and interpreted the data.

Aftab Shoukat: Contributed reagents, materials, analysis tools or data; Wrote the paper.

Farid T. Nusairat: Performed the experiments; Wrote the paper.

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Competing interest statement

The authors declare no conflict of interest.

Additional information

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