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ORIGINAL RESEARCH

Structural equations model to analyse the critical variables related to smart card technology adoption in South African public healthcare

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Implementation of healthcare information systems is one of many public healthcare technological improvements. In this study, the important factors relating to the adoption of smart card technology (SCT) in public healthcare are analysed. The study used structural equation modelling (SEM) to estimate modelling methods and the range of potential applications in the field of healthcare. This study aimed to develop a model of structural equations that summarises the critical success factors which are related to the adoption of smart card technology in South African public healthcare. The study began by presenting the reviewed literature and demonstrating which of it was based on variables taken from the determined underlying ideas. The questionnaires were distributed to healthcare professionals at Steve Biko Academic Hospital, Kalafong Tertiary Hospital, Pretoria West and Tshwane District Hospitals. According to the suggested model, critical factors included behavioural intention, system use, information quality, service quality, communication, compatibility and trialability. However, effort expectancy, social influence, facilitating conditions, user attitude and user satisfaction were not supported by the study. Confirmatory factor analysis was created using the measurements collected as the results. The outcomes supported the essential role of healthcare professionals in hospitals in order to fully implement SCT. This would afford patients the opportunity to access better healthcare services. Based on the information gathered from samples, the study made the assumption that the findings may be confirmed in a variety of fields, including those outside of healthcare. This study will contribute towards the adoption of smart card technology in the South African public healthcare context using the findings obtained from structural equation modelling.

Keywords: Adoption, public healthcare, healthcare professionals, smart card technology, hospitals

Strukturelevergelyking-model om die kritieke veranderlikes wat verband hou met die aanvaarding van slimkaarttegnologie in Suid-Afrikaanse openbare gesondheidsorg te ontleed: Implementering van gesondheidsorginligtingstelsels is een van vele tegnologiese verbeterings in openbare gesondheidsorg. In hierdie studie word die belangrike faktore wat verband hou met die aanvaarding van slimkaarttegnologie (SKT) in openbare gesondheidsorg ontleed. Die studie het strukturelevergelyking-modellering (SVM) gebruik om modelleringsmetodes en die verskeidenheid potensiële toepassings in die veld van gesondheidsorg te beraam. Hierdie studie het ten doel gehad om 'n model van strukturele vergelykings te ontwikkel wat die kritieke suksesfaktore opsom wat met die aanvaarding van slimkaarttegnologie in Suid-Afrikaanse openbare gesondheidsorg verband hou. Die studie het begin deur die literatuur waarvan 'n oorsig gedoen is aan te bied en te demonstreer watter daarvan gebaseer was op veranderlikes wat uit die vasgestelde onderliggende idees geneem is. Die vraelyste is aan gesondheidsorgberoepslui by die Steve Biko- Akademiese Hospitaal, Kalafong- Tersiêre Hospitaal en die Pretoria-Wes- en die Tshwane-distrikshospitaal versprei. Volgens die voorgestelde model sluit kritieke faktore gedragsvoorneme, stelselgebruik, inligtingskwaliteit, dienskwaliteit, kommunikasie, versoenbaarheid en beproefbaarheid in. Inspanningsverwagting, sosiale invloed, fasiliterende toestande, gebruikershouding en gebruikerstevredenheid is egter nie deur die studie ondersteun nie. Bevestigende faktoranalise is geskep deur die metings wat ingesamel is as die resultate te gebruik. Die uitkomste het die noodsaaklike rol van gesondheidsorgberoepslui in hospitale ondersteun ten einde SKT ten volle te implementeer. Dit sal aan pasiënte die geleentheid bied om toegang tot beter gesondheidsorgdienste te verkry. Op grond van die inligting wat uit steekproewe versamel is, het die studie die aanname gemaak dat die bevindinge in 'n verskeidenheid velde bevestig kan word, waaronder ook velde buite gesondheidsorg. Hierdie studie sal bydra tot die aanvaarding van slimkaarttegnologie in die Suid-Afrikaanse openbaregesondheidsorg-konteks deur gebruik te maak van die bevindinge van strukturelevergelyking-modellering.

Sleutelwoorde: Aanvaarding, openbare gesondheidsorg, gesondheidsorgberoepslui, slimkaarttegnologie, hospitale

Introduction

The medical and healthcare sectors contribute significantly to raising living standards and quality of human life (Mardani et al., 2019). The majority of patient care services are now provided through health information technologies (HITs), such as electronic medical record (EMR) systems, patient health record (PHR) systems, and technical equipment. There is no theory that explains how HIT success affects how patients perceive the quality of their care, despite the ongoing spread of HITs within the healthcare industry. Significant progress has been made in understanding the effectiveness of HITs and their influence on patient care outcomes such care quality, patient happiness, patient empowerment, and greater chance of drug adherence (Callen, Paoloni, Li, Stewart, Gibson, Georgiou, Braithwaite & Westbrook, 213;Sherifali , Nerenberg, Wilson, Semeniuk, Ali MU, Redman & Adamo, 2017). The capability of sharing medical information electronically is a key enabler of coordination in a health care system. Sharing medical records enables prompt treatment delivery, which benefits the patient. Researchers have demonstrated that sharing medical information is, thus, a helpful service for patients (Baird & Raghu, 2013). Healthcare professionals must therefore respond to patients' requests for services and constantly provide a greater quality of service. As regards the benefits of this study, hospitals may be found benefiting from the use of information and communications technology to increase their competitiveness in the delivery of healthcare (Awiagah, Kang & Lim, 2016).

Most developed countries such as Slovenia, Hungary, Spain and France reported that positive use of ICTs in healthcare facilities led to better healthcare delivery (Stanimirović, 2015) encompassing the construction of a national health information system (NHIS. Utilising health facility data at all levels is crucial, but it is not widely used in developing countries, such as Ethiopia, Zimbabwe, South Africa, Botswana and many others (Asemahagn, 2017). Due to the numerous problems encountered, implementing health information systems in healthcare in poor countries takes time, and the fact that projects are left unfinished is a problem that hampers the provision of public healthcare. Furthermore, poor record-keeping continues to create unnecessary delays for patients. Patient's folders go missing or are misplaced from time to time, and instead of informing the patient, healthcare professionals simply let the patient wait. In the worst situations, the patient's medical history is lost completely, which may lead to further challenges, such as incorrect diagnoses and in extreme instances, death (Sethia, Gupta & Saran, 2019).

South Africa has the potential to improve the delivery of healthcare services while also enhancing efficiency and lowering the costs of manual systems currently in use. However, the Department of Health in South Africa requires more advanced research to improve patients' health by attending to all the issues. Smart card technology has a number of benefits, including quick and accurate patient identification as well as simple access to patient medical records. Therefore, this technology gives accurate clinical information rapidly and effectively while maximizing the safety and security of patient identity (Kahn, Aulakh & Bosworth, 2009). It also makes it easier for national registries to be created, which could ultimately lead to better health service delivery (Noori , Ghazisaeedi, Aliabad, Mehdipour, Mehraeen, Conte, Safdari, 2019; Niakan, Mehraeen, Noori & Gozali, 2017).This research used the structural equation model to analyse the critical variables related to smart card technology adoption in South African public healthcare.

Literature Review

A physical card with an incorporated integrated chip that serves as a security token is known as a smart card. Smart cards can be composed of metal or plastic and are normally the same size as a driver's licence or credit card. Ray, Dash & Kumar (2020) state that smart card technology is an embedded integrated circuit, a secure microcontroller or comparable intelligence and internal memory or a single memory chip with no other functions that make up a smart card. Furusa & Coleman (2018) pointed out that for eHealth to be implemented in Zimbabwe, doctors had to demonstrate their capacity to use the technology. For this reason, doctors have been required to learn how to use eHealth technologies in public hospitals, which require hardware and software that cannot be avoided during treatment. As a result, it is comparable to the implementation of smart card technology in South African public healthcare. The adoption and use of SCT by healthcare professionals, among other things, ease the tasks of record-keeping of patients' information, including the filing, storage and information on the sequence of medication (Sahay, Nielsen & Latifov, 2018; Malungana & Motsi, 2023). In achieving the use of SCT for healthcare professionals, the eHealth strategy has become one of a number of promising platforms (Cheng & Huang, 2013).

Technology adoption cannot be separated from implementation science, two aspects that are closely related. Technology adoption focuses on how end-users adopt technology, while implementation describes the interventions and variables that help promote evidence-based practice (Schoville & Titler, 2015). An eHealth card was launched in Nigeria. The card receives input from an application and provides an output. However, due to large populations in hospitals, healthcare professionals continue to employ the paper-based method of healthcare delivery, which causes many challenges for implementation of the smart identity card (Adebayo & Ofoegbu, 2014). In particular, the smart card requires each patient to authenticate themselves to receive better healthcare service (Alam & Ali, 2016).

Based on the literature review, this study was aimed at analysing the critical variables related to SCT adoption in South African healthcare by accessing various variables from three different models/theories, namely the healthcare unified theory of acceptance of user technology model (HUTAUT) (2018), the DeLone and McLean IS success model (2003), and the Diffusion of Innovation theory (DOI). In this study, seven identified hypotheses stated in table 3, had a direct effect on the analysis of the critical variables related to smart card technology adoption in South African public healthcare (Malungana & Motsi, 2023).

Research Methodology

This study involved quantitative research. Secondary information was gathered from related theories and concepts of this study. Primary information, however, was sourced using the close-ended questionnaire which had been populated by the healthcare professionals forming the sample. SPSS version 26 and Amos software were used to gather data. This study used dependent and independent variables, and mediating variables. The study factor variables were: 12 for the HUTAUT Theory (effort expectancy, performance expectancy, social influence, facilitating conditions and behavioural intention), for the D&M IS success model there were four (service quality, system quality, information quality, user acceptance) and for DOI theory there were three (compatibility, communication and trialability). Purposive sampling was applied for this study to collect data from healthcare professionals. The population of this study was at Steve Biko Academic Hospital, Tshwane District Hospital, Kalafong Tertiary Hospital and Pretoria West Hospital in the City of Tshwane Metropolitan District and sampling was done there.

Assessment of Research Tools

The validity of the questionnaire was examined among 460 healthcare professionals. In this study, the questionnaire was limited to responses from healthcare professionals, whereas 50 of the 460 healthcare professionals were obtained from the pilot study to validate the questionnaire. According to Ahmad, Ibrahim and Bakar (2018), the acceptable reliability coefficient is above 0,700. The Cronbach's alpha value was more than 0,7 after reliability and validity testing, indicating that all the data submitted and analysed was reliable.

Data Analysis

In this study, the data analyses were divided into three: (1) analyses based on information from the representative samples from the distribution frequency and percentage; (2) analyses based on information from the 12 independent variables; and (3) analyses based on three moderating variables for the adoption of SCT in public health. Confirmatory factor analysis (CFA) was used in the study to test the hypotheses and examine how well the model fitted the data. As a result, the structural equation model (SEM), which generated path analysis for testing the model and hypotheses, was used to test the hypotheses model.

Results

A total number of 486 questionnaires were distributed, and 406 were returned and analysed for the study. Therefore, the total results of the analysis are based on tested hypotheses, which are presented in table 3 of the study.

Data Analysis

In this study 406 data sets from health professionals were collected for data analysis. These samples included male and female working groups from the identified hospitals, and they stated their educational level, the ward in which they were working, and their experience and knowledge of smart card technology adoption at public hospitals.

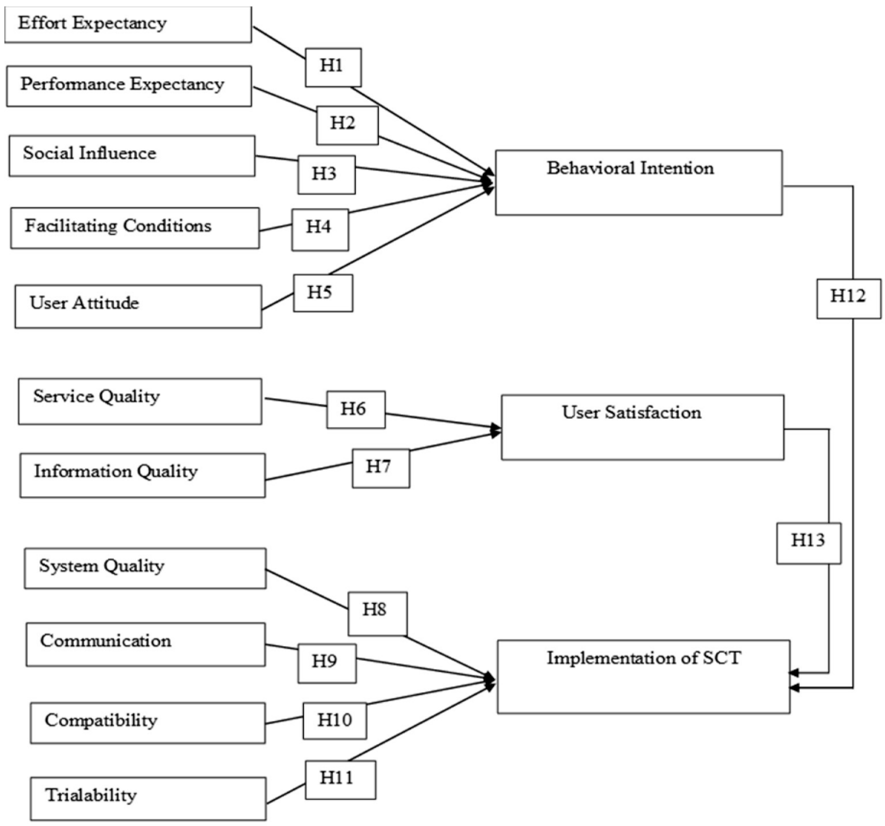

Figure 1: Framework of the critical variables in smart card technology

Table 1: Data Analysis for the Study

Description	Percentage
Sex:	
Male	37%
Female	63%
Age:	
Below 25	3%
25–30	33%
31–40	53%
41–50	8%
50 plus	3%
Department:	
Emergency	20,2%
Midwifery	31,5%
Paediatric	10,6%
Neonatal	4,9%
Surgical	32,5%
Others	0,2%
Highest qualification:	
Grade 12 or below	4,7%
Diploma	32,5%
Degree	52,5%
Postgraduate	9,4%
Others	1,0%
Work Experience	4,7%

Hypothesis Testing

In this study, the CFA and analysis are shown in figure 2. These results showed a good fit model with empirical data within the expected level of the study. In summary, the model's efficacy for the critical adoption of SCT in South African public health confirms the hypotheses. As a result, the model was used to measure the applied SEM measurement so as to analyse its future influence on the adoption.

Confirmatory factor analysis was run in AMOS 23.0, using the maximum likelihood estimation. This was done to confirm the components or variables concluded after the exploratory factor analysis. According to Arbuckle (2014), factor loadings with critical ratios (CR) above 1,96 are significant at the 0,5 level and show a reasonable fit to the data. The CFA indicated that the critical ratios are significant because they were all above 1,96. Results from the CFA showcase the factor loadings and their corresponding ratios. After the removal had been done the final CFA model was run. The model showed acceptable indices: x2= 4,490, df = 3; chi sq/df = 3,163; P = 0,122; GFI = 0,955; AGFI = 0,905; CFI = 0,976; RMSEA = 0,43; PCLOSE = 0,316. The final CFA model presented 47 items and 13 variables. This demonstrates the thoroughness of the iterative process. It is important to note that the EE variable was left with two items; however, due to its theoretical significance and the content validity of the two items, it was decided that the variable be maintained.

Following the development of the structural model, the relationships that existed between constructs were examined. The summary extract from the AMOS output for the standardised significance levels obtained after running the structural model is shown in table 2. These levels depict the hypothesised relationships between the latent variables that comprise the underlying causal structure of SCT implementation. Wahab, Kadir & Tomari (2014) recommended that a threshold of 1,96 be obtained for the values of the critical ratio (CR) to determine the significance of the hypothesised relationship. This means that for a hypothesis to be significant or supported, its constructs must have a critical ratio value greater than 1,96 otherwise the hypothesis was rejected. The results of the hypotheses tests are shown in table 3 of the Structural Equation Model.

Discussion

The study provides unique findings in a wide range of fields. Initially, the significance of the traditional adoption factors was examined, and several of these aspects' crucial importance emerged. The use of smart card technology in South African public healthcare is influenced by structural equation modelling of the research variables (Malungana & Motsi, 2022). In addition, the structural equation modelling (SEM) is regarded as a more significant second-generation multivariate statistical technique (factor analysis and regression). When the data is abnormal, SEM is typically used. SEM is more practical than conventional multivariate statistical methods (Zahid & Din, 2019). In order to apply this, the SEM analysis was conducted utilising widely established characteristics such behavioural intention, system use, information quality, service quality, communication, compatibility and trialability.

Latent Variable

The main objective of this study was to analyse the critical variables related to smart card technology adoption in South African public healthcare using the structural equations model. The test of Sallehudin, Bakar, Ismail, Razak, Baker and Md Fadzi (2020) brought an understanding of the strength of the relationship between dependent and independent variables and either confirmed or did not confirm each of the hypotheses. In addition, hypotheses were used to estimate the structural model aimed at testing this study's research hypothesis (Kruszyńska-Fischbach et al., 2022) these consequences pose a great challenge for patients and healthcare providers, i.e., the limited personal contact with medical professionals. This can be eased by new digital technology. While providing solutions to many problems, this technology poses several organizational challenges for healthcare system participants. As the current global situation and the outbreak of the humanitarian crisis in Europe show, these and other likely emergencies amplify the need to learn the lessons and prepare organizations for exceptional rapid changes. Therefore, a question arises of whether organizations are ready to use modern e-health solutions in the context of a rapidly and radically changing situation, and how this readiness can be verified. The aim of this article is to clarify the organizational e-heath readiness concept of Polish primary healthcare units. This study employed the quantitative approach, based on statistical and mathematical techniques that identify facts and causal relationships. Various data patterns were considered when collecting data. It also involved creating hypotheses and generating theories that could be confirmed by studies. This confirmation approach began with a hypothesis regarding the occurrence of a specific phenomenon and then built a predictive model based on the theory.

In this study, the researcher performed empirical research and investigation to put the argument to the test and determine if the evidence backed it up, establishing the causal theory. Addai and Arthur (2020) stated that performance expectancy was proven by many authors and researchers to be the key belief factor that influenced positively the decision to use or accept new technology. However, this study highlighted that performance expectancy level could not be regarded as the critical variable for SCT adoption in South African public healthcare. Performance expectancy was found to have a high positive skewness value of 0,308, meaning that most respondents disagreed or strongly disagreed with the questions relating to its role in the adoption of SCT in public healthcare.

For reliability, the performance expectancy scale was removed because none of the items were found to hold well with any other. Low correlations (all below 0,100) showed that the scale was not internally consistent. It was therefore found appropriate to remove the scale at this stage of the analysis. The performance expectancy hypothesis (H2) was dropped due to its low reliability (see Table 2). Five of the study's hypotheses were not supported, namely effort expectancy (H1), social influence (H3), facilitating conditions (H4), user attitude (H6) and user satisfaction (H7). To drive the research towards the adoption of SCT in healthcare, negative skewness was highest for effort expectancy (-0,54), followed by user attitude, social influence, information quality, behavioural intention and SCT implementation (-0,477, -0,282, -0,250, -0,222 and -0,213 respectively). The least negative skewness values were -0,015 and -0,056 respectively for system quality and trialability. In summary, respondents *agreed* or *strongly agreed* that the factors investigated in this study played a role in the implementation of SCT in healthcare institutions.

A structural equations model to analyse the critical variables related to smart card technology adoption in South African public healthcare (Figure 2 and Table 3) was then developed by combining all of the accepted hypotheses: behavioural intention (H5), system use (H8), information quality (H9), service quality (H10), communication (H11), compatibility (H12) and trialability (H13).

Hypothesis (H5), which suggested that behavioural intent had a significant impact on SCT implementation, was supported (β = -0,209, p<0,001, R^2 = 0,75). Furthermore, additionally implying that the two variables had an inverse relationship, hypotheses (H6) and (H7) (user attitude and user satisfaction effect on implementation of SCT) were not supported (β = 0,480, p=0,741, R^2 = 0,75 and β = -0,317, p=937, R^2 = 0,75 respectively). Hypotheses (H8) to (H13) were all supported. It was found that system use (β = 0,209, p<0,001, R^2 = 0,75), information quality (β = 0,557, p<0,001, R^2 = 0,75), service quality (β = 0,562, p<0,001, R^2 = 0,75), communication (β = 0,211, p<0,001, R^2 = 0,75), compatibility (β = 0,419, p<0,001, R^2 = 0,75) and trialability (β = -0,020, p<0,001, R^2 = 0,75) variables had a significant impact on the implementation of SCT.

According to the findings of this study, trialability impacts the implementation of SCT negatively. In addition, factors impacting the implementation of SCT in public healthcare have been thoroughly investigated; therefore, the use of structural equation modelling (SEM) for study analysis has gained extra interest. Furthermore, the research model considered applying the SEM to bring robustness to the statistical technique. This study also further explored other areas where the SEM was applied. It was found that SEM is no longer limited to dealing with complex research challenges in traditional research topics; it can also be a helpful tool for construction academics and technicians to assess the acceptance, use and success of newly developed technologies (Xiong, Skitmore & Xia, 2015).

Table 2: Performance Expectancy

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item – Total Correlation	Cronbach's-alpha if Item Deleted
PE2	125542	1 295	0,079	-0,249a
PE3	12 8350	1 936	-0,279	0,389
PE4	12 6034	1 302	0,090	-0,265a
PE5	12 8596	1 326	0,093	-0,262a

Current reliability (α) = -0,061
Decision: to remove the variable completely

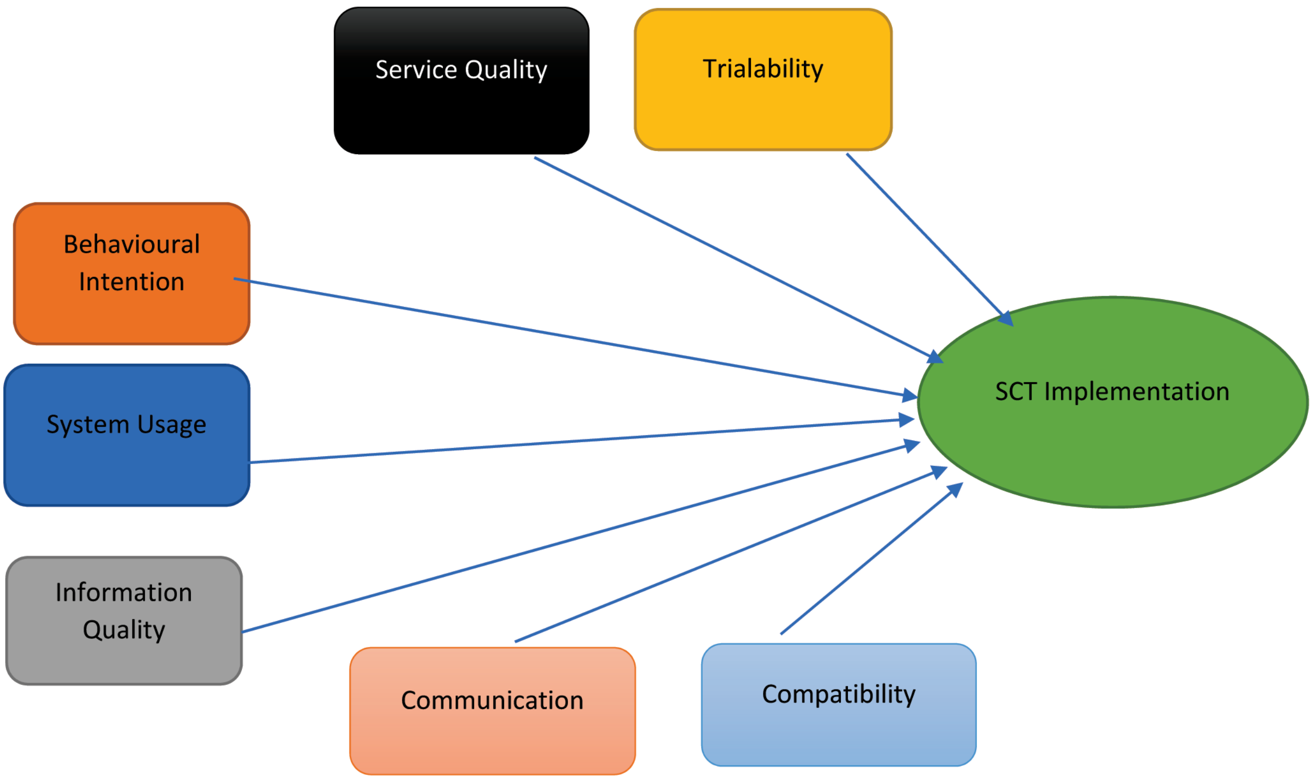

Figure 2: Final SCT implementation framework

Table 3: Hypotheses testing

Hipothesis	Path			Standardised Estimate	S.E.	C.R.	P	Decision
H1	IM	←	EE	-0,575	0,025	0,174	0,862	Unsupported
H2	IM	←	PE	*Hypothesis dropped due to low reliability*				
H3	IM	←	SI	-0,054	0,032	0,148	0,882	Unsupported
H4	IM	←	FC	-0,208	0,023	0,203	0,840	Unsupported
H5	IM	←	BI	-0,209	0,063	-5 287	***	Supported
H6	IM	←	UA	0,480	0,019	0,331	0,741	Unsupported
H7	IM	←	US	-0,317	0,028	0,078	0,937	Unsupported
H8	IM	←	SU	0,209	0,029	5 363	***	Supported
H9	IM	←	IQ	0,557	0,047	8 883	***	Supported
H10	IM	←	SQ	0,562	0,032	6 436	***	Supported
H11	IM	←	C	0,211	0,046	7 538	***	Supported
H12	IM	←	CP	0,419	0,081	6 021	***	Supported
H13	IM	←	TR	-0,020	0,090	7 437	***	Supported

*** = p<0,001

36 responses were removed due to unengaged responses. To check for unengaged responses, the standard deviation of the responses was checked according to the rows. All rows whose standard deviations were below 0,5 were removed (Belayneh et al., 2017). The normality of the data was checked using skewness and kurtosis methods as suggested by Anwar, Noorman Masrek and Johari Abdullah Sani (2017). The variables' normality was acceptable when the skewness and kurtosis fell between –2 and +2. Items that violated the principles of the assumption of normality were removed (EE1, EE3, PE1, PE6, SI2, SI6, FC5, BI5, SQ1, CP5, TR2 and IM3).

The degree of approximation of repeated measurements under the same conditions is referred to as scale reliability. It is used to assess scale consistency and stability, and it can change over time and among respondents. External and internal reliability are both included in the term reliability. The former refers to the consistency of the constituents in the scale's items, while the latter pertains to inter-rater reliability. At this stage, the internal consistency of the scale items was assessed. The acceptable reliability coefficient was found to be above 0,700. In this section, the reliability of all the scales was presented to demonstrate chronologically the reason for the removal of some scales and even a variable. In this section, the Item-Total statistics tables were presented, including the prevailing and final reliability coefficient after some items had been removed.

Factor analysis was used for determining the nature of the latent constructs that underpin the variables of interest (Bandalos & Finney, 2019). Factor analysis, according to (Mukherjee, Sinha & Chattopadhyay(2018) seeks to identify underlying variables, or factors, that explain the pattern of correlations within a set of observed variables or construct items. One common goal of factor analysis is to produce a small number of factors that can be used to replace a much larger number of variables (Amaral et al., 2013)we test the small molecule flexible ligand docking program Glide on a set of 19 non-α-helical peptides and systematically improve pose prediction accuracy by enhancing Glide sampling for flexible polypeptides. In addition, scoring of the poses was improved by post-processing with physics-based implicit solvent MM- GBSA calculations. Using the best RMSD among the top 10 scoring poses as a metric, the success rate (RMSD ≤ 2.0 Å for the interface backbone atoms. Factor analysis is a data reduction technique that attempts to identify only a small number of variables (Chattopadhyay, 2018). This means that at the end of factor analysis, the researcher is left with variables that explain most of the variance, while those that explain the least variance are discarded.

The study extracted factors using the principal components analysis (PCA) method with the aim of finding the sequence of orthogonal factors that represent the directions of the greatest variance Ejaz, Islam & Sarker (2019). In addition, PCA was used because it can form uncorrelated linear combinations of the observed variables. It is also used to obtain the initial factor solution and can be used when a correlation matrix is singular. As a factor rotation method, a direct Oblimin method was used because the literature suggested some theoretical grounds that implied that the factors in this study are related or correlated during theory development. The researchers in this study chose to display the coefficients in order of size and to suppress coefficients with absolute values less than 0,4 (Nicol et al., 2021) The following output was extracted and explained: correlation matrix, Kaiser-Meyer-Olkin and Bartlett's test.

Exploratory factor analysis (EFA) was conducted using maximum likelihood with Promax rotation to determine if the items loaded well on the variables and correlated adequately. Maximum likelihood estimation was chosen to determine the unique variance among items and the correlation between factors. Pallant, (2020) highlights that a maximum likelihood also provides a goodness of fit test for the factor solution. Promax was chosen due to Bartlett's test of sphericity and the KaiserMeyer-Olkin (KMO) measure of sampling adequacy was assessed. The results revealed a KMO of 0,949 and the Bartlett's test was significant at α=0,000, with a chi-square of 20225,791, indicating the suitability of conducting exploratory factor analysis (Samuels, 2016). Items that did not show high loadings were removed (EE4, IQ6, SYQ4, and SYQ5).

Conclusion and Recommendation

This study concluded that smart card technology has a direct impact on adoption in public healthcare. The structural equation model revealed that seven variables of the SCT directly influence the adoption. However, performance expectancy was found to have no direct effect on the adoption of the SCT. Based on the results of this study seven critical factors, namely behavioural intention, system use, information quality, service quality, communication, compatibility and trialability, need to be considered in the adoption of SCT. This study focused on quantitative research, and it recommends that change management activities that focus on training may be used to gain more in-depth information for healthcare professionals. As a result, training factors should be considered for future studies.

Dates

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