Article

Impact of IoT towards Achieving Smart Primary Healthcare Building Facilities in Gauteng, South Africa

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Abstract: Smart primary healthcare building facility services capture a new level of process and operational data through advanced monitoring, enabling experts to use the building facilities to produce significant and efficient healthcare service delivery within the individual spheres of influence. This study assessed the impact of IoT services on achieving smart primary healthcare building facilities in the rural area of South Africa to enhance primary healthcare delivery. The study identified three (3) basic constructs of IoT services that comprised the application of IoT location recognition and tracking services, the application of the IoT high-speed communication network-based services, and the application of IoT-based services. The study is quantitative, and a questionnaire was used to collect data from the project managers and healthcare practitioners working with the primary healthcare agency in South Africa. The study found a variable degree of impact between the three (3) IoT constructs and the achievement of primary healthcare building facility services in South Africa. The study recommends adopting IoT essential services for achieving smart primary healthcare building facility services in the rural areas of South Africa and other developing countries facing similar primary healthcare delivery challenges.

Keywords: smart primary healthcare; building; Construction; South Africa

1. Introduction

With the advancement in information technology (IT), smart healthcare buildings have gradually come to the fore. Smart healthcare building facility services use a new generation of IT gadgets like the internet of things (IoT) which transform major challenges faced in the traditional medical service delivery in an all-around way, making healthcare delivery efficient, convenient, and personalized. The concept of smart healthcare building facility services entails the application of smart technologies that support smart healthcare building facility services and introduce the status of smart healthcare in several necessary fields (Yuan et al., 2022).

Most healthcare digitalisation literature focuses on the benefits, barriers, and determinants of adopting information and communication technology (ICT) based solutions within healthcare building facilities. But evaluating the impact of IoT essential services towards achieving primary healthcare building facility services remains problematic considering the issues associated with traditional healthcare service delivery in developing countries, such as dilapidated building facilities, poor coordination of healthcare services etc. (Wassie, Gintamo, Mekuria, & Gizaw, 2022).

Similarly, the problems associated with data gathering for the primary healthcare building facility entail the regular methods of acquiring data, poor data analysis methods and deployment for real situations, poor safety pointers, inferior quality assurance of the data as a result of wrong methodology, logistics, financing, poorly written manuals, timing, etc. Jaafar et al. (2021) stated that healthcare building facility services are globally charged with multiple inherent risks because many users are vulnerable to tragic events.

However, Yuan et al. (2022) added that healthcare buildings are also faced with the problems of data gathering of indoor environments and thermal comfort.

A study conducted on healthcare organization performance factors in private clinics of Addis Ababa in Ethiopia by Wassie, Gintamo, Mekuria, and Gizaw (2022) found that a figure of about 61.2% of the clinics experienced poor healthcare waste management services. Then, the study reported that 56.8% of the clinics experienced poor waste segregation services. Also, 55.0% of the clinics had poor waste collection methods. Poor waste transportation method of the clinics accounted for about 85.6% and about 63.3% was accounted for because of poor waste storage service. The problems of poor waste treatment methods of the clinics accounted for about 61.9% and lastly, 57.9% was for poor disposal system.

Similarly, in the UK, Wanigarathna et al. (2019) investigated the relationship between digital capabilities and building information modelling (BIM). The study integrates a vast of information which enhances the decision-making of built asset management (BAM), especially during the in-use phase of the healthcare facility. The results of the study indicated that BIM is having the potential to ease better and well-versed decision-making of the BAM through the integration of a variety of data that are related to the physical condition of the built facility. However, the significant shortcomings of using BIM for data gatherings are its incompatibility, i.e., not commonly and universally used among construction professionals and the legal issues attached to the software applications. Then, the cost of the software requires considerable investment.

In a different study in the Philippines, Dela Cruz and Tolentino (2021). found that the problems associated with poor information gathering in the management of public healthcare facilities originated mainly because of poor financial resources allocation, improper deployment of the right materials, and technologies like IoT. Also, Schuchat, Covid, and Team (2020) stressed that the planning process of the United States (US) healthcare facilities is deficient in the clear mandate of the beneficiaries in terms of developing political, financial and legal powers on the process.

Similarly, Jia et al. (2019) examined the state-of-the-art healthcare facility projects which identify the process of implementation of IoT for the management of the healthcare building facility. The results of the study indicated that the IoT technologies significantly enhanced the management process of healthcare construction and operation. The IoT impacted the facility through the facilitation of high-quality services, provision of efficient functionalities, and enhancing sustainable infrastructure facilities. However, the study did not assess the level of the impacts of the technology on achieving data gathering and analysis for primary healthcare facilities in developing countries.

Moreover, Zhao and Jiang (2018) introduced Insect Intelligent Building (I^2B), which operates based on IoT. The main features of the technologies were developed from agent models. The I^2B used space units and control devices that were developed from the model. This connects between the devices and the surrounding spaces i.e., control devices (insect) for each space unit or each control device with six data ports (legs). The control devices communicate with each other via the data ports based on the developed model. The network performs various operations within the building facility and computes tasks that run on smart controllers and depends on the associations among neighbouring controllers to achieve the desired effects of the commands. The main shortcomings of this system are the problem associated with the standard description of the device and the unit space. Then, the issue of the systematic process that changes the facility control programs into parallel computing tasks that would be successively on smart nodes and the communication procedures.

Therefore, the current paper will assess the impacts of IoT towards achieving smart primary healthcare building facility services through the assessment of significant technologies suitable for achieving smart primary healthcare building facilities with the view to enhance healthcare delivery in the rural areas of South Africa.

The following objectives of the paper are:

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- To explore the major IoT technologies fostering smart primary healthcare buildings facility services
- To assess the impact of the IoT technologies services in achieving smart primary healthcare buildings

1.1. Literature Review

The literature review for this paper was done under smart building facilities, technologies influencing smart healthcare building facilities and IoT technologies fostering smart healthcare buildings.

1.2. Smart buildings facilities

The global smart building market is growing unabated which is driven by the IoT and a new breed of technologies. The smart healthcare building facility remains an essential component in improving healthcare infrastructure. Smart healthcare building facility provides healthier energy efficiency for the facility and controls the safety aspects of the healthcare facility including the framework for the comfortability of residents and enhanced quality of life and serviceability (Huseien & Shah, 2022). The definitions of smart building facilities are proposed and focused mainly on energy features linked to the concept of a "smart grid". A healthcare building facility that incorporates smart management systems and huge storage of data and analytics facilitates easy management of energy in the facility. The electrical facilities on the grid that studies the pattern and behaviours within the facility are regarded as smart/intelligent building facility system. Consequently, the management process of such devices is smart/intelligent via the adoption of IoT technologies (Kwon et al., 2022).

Generically, a smart healthcare facility comprises three (3) levels that include: The level of the infrastructural data inputs, which embodies all the sources of the data collected by the devices such as consumed energy, level of humidity, indoor/outdoor temperatures, safety alarm activation and deactivation and so on. Then, the level of the facility system signifies the fundamental of the smart system, because this permits the gathering, processing, assembling and storage of the information in a NoSQL database system. Accordingly, the system permits the utilization of the collected data for the extraction of knowledge by data mining systems. The process of automatic learning through artificial intelligence (AI) algorithms (Umair, Cheema, Cheema, Li, & Lu, 2021).

In the age of IoT, Khan and Salah (2018) described the basic features of a smart healthcare building facility as any healthcare building with interoperability of the building facilities and having a mobile integrated solution, while Wassie et al. (2022) added that smart healthcare building facility should have the features such as digitisation of information and established unified system of the communication system (Kwon et al., 2022). Smart building facilities are linked online. Greater attention is also being paid to integrated building automation in renovation and new construction buildings. These buildings where smart technology is applied are called smart buildings.

1.3. Technologies influencing smart healthcare building facilities (SMAHEAL)

The acronym “SMART" means “Self-Monitoring Analysis and Reporting Technology.” This is a technology that provides reasoning alertness to objects, by using innovative technologies like IoT, artificial intelligence (AI), machine learning (ML) and extensive analysis of the collected data that provides intellectual understanding to the facilities that were earlier regarded as lifeless (Bellini, Nesi, & Pantaleo, 2022). Smart technologies are networks of devices that use IoT sensor devices and software that are connected online. This system brings the static physical facility to life. The devices provide significant value and are sustainable, mountable, and automated. On the other hand, IoT is a significant technological network device that uses internet connectivity on sensor devices and software that animate static physical facilities (Malik et al., 2022).

Baqer et al. (2022) described that smart mobile and other smart appliances within the healthcare building facility are critical IoT technologies that support the achievement of primary healthcare building facilities in developing countries. The Smart connected devices in the primary healthcare building facility are commonly and remotely controlled with, LTE, Bluetooth, cellular connectivity and Wi-Fi (Channi & Kumar, 2022).

According to Kwon et al. (2022), smart primary healthcare building facilities are commonly categorized into three (3) constructs namely: Services based on location recognition and tracking technology, which evaluates and also monitors the location of any data in the facility based on short-range communication technology; the second construct is the high-speed communication network-based services which is an install wireless communication technology; lastly the construct of IoT-based services which is used to link IoT devices that were embedded with sensors and communication functions to the internet.

1.4. IoT Location Recognition and Tracking Services (IoT-LORE)

IoT facility services are usually achieved by measuring and monitoring the location-based information of any functional facility within a healthcare building space with the aid of location recognition and tracking technology constructed on short-range communication technology (Kwon et al., 2022; Verdejo et al., 2021). The major technologies associated with IoT in the management of healthcare building facilities are Bluetooth technologies, beacons technologies, Wi-Fi, technologies Zigbee technologies, RFID and GPS technologies, A-GPS technologies, barcodes and QR codes technologies and the ultra-wide-band and communication technologies e.g., the 5G technology (Kwon et al., 2022). With the introduction of a tracking system within the healthcare building facility for real-time assets in healthcare services using the IoT devices, medical institutions enhance the effectiveness of logistics management that relates to the healthcare building facility and hence improve the workflow of medical staff in the facility (Birje & Hanji, 2020). In the US healthcare system where smart infusion pump was introduced with involved RFID, this enhances the productivity and effectiveness of healthcare building facility through the reduction of about 80% of the time used by the medical staff to locate any facility within the healthcare centre using real-time location monitoring (Kwon et al., 2022)

1.5. IoT High-Speed Communication Network-Based Services (IoT-HISB)

IoT-HISB likes the 5G network and the Wi-Fi 6 network that delivers healthcare building facilities with internet services that overwhelmed the shortcomings of real information gathering and analysis processes. These systems of communication are constructed on wireless communication technology such as the Wi-Fi 6 technology, as one of the highspeed communication network services is mainly used in healthcare buildings which is appropriate for healthcare buildings where there is high traffic involving regular changes of environment (Schuchat et al., 2020; Singh & Mahapatra, 2020). The introduction of orthogonal frequency-division multiple access (OFDMA) technologies that combines multiple users at different times and requirements to get access to a single access point simultaneously in a healthcare building reduces the transmission waiting time.

The application of Wi-Fi 6 technologies helps in the accurate analysis of the records of patients within the building facility. The real-time data also aids in improved treatment outcomes through precise administration of medication. This is achieved by an objective decision-making procedure according to the accurate and current patient database (Wassie et al., 2022). The technology of Wi-Fi 6 aids medical devices, like infusion, pumps with adjustable data to transfer times and reduces usage overlap and improves the efficiency of facility operation and maintenance. This is also achieved through OFDMA by allowing about thirty (30) different facility devices to use the same infusion pump and channel without changing orders (Yan, 2019; Zhao & Jiang, 2018).

1.6. IoT-based Services (IoT-BAS)

IoT-BAS is a technology that links different facilities entrenched with sensor devices and communication connected to the Internet. The technology entails facility identification, construction of the network, attached sensor devices and control (Kwon et al., 2022). The introduction of IoT in healthcare building facilities for a smart healthcare building could be achieved via leveraging the sensor devices, cloud computing, methods of connection, databases, internet protocols, and analytics as infrastructure and using different systems together (Wassie et al., 2022). IoT technologies and smart healthcare building facilities are used for different reasons like the reduction in the maintenance costs of healthcare building facilities, reducing operating costs of machinery and equipment in the healthcare services, enhancing patients treatment through the reduction of diagnostic delays, increasing staff and patients comfortability, detecting deterioration early in the healthcare buildings, enhancing general safety for both patients and staff, providing energy efficiency in the healthcare buildings and general improvement in the profitability (Kwon et al., 2022).

IoT enables the automation and detection of various defects in healthcare buildings for prompt measurement and remedial services. The IoT-based vital measurement sensor devices have been contracted and attached to the building facilities to aid measurements of any identified defect (Karthick, Kermanshachi, & Ramaji, 2022). Kang et al. (2019) stated that Barcodes technologies, RFID technologies, fingerprint/iris/face recognition technologies, and ultrasound-based recognition technologies are used in smart healthcare buildings to deliver better and faster services. The commonly used IoT-based system is the RFID technology that is used for healthcare building facility management and medical services (de la Torre Díez et al., 2019; Jackson, 2002).

2. Materials and Methods

This study reviewed papers exploring the relationship between IoT and smart building infrastructure applications. In addition, the study aimed to assess the impact of different IoT services on achieving smart healthcare building facilities. Subsequently, based on the literature, a conceptual framework that binds the relationship between different IoT services and the smart primary healthcare building facilities was developed, hence the questionnaire used to collate the data for this study had four (4) study constructs. The constructs consist of three (3) constructs of IoT services and one (1) construct of the factors of the smart primary healthcare building facility. Hence, this study adopted a quantitative design (McNabb, 2017). The area of this study is smart healthcare building facilities.

A randomly selected group of 750 project managers and healthcare practitioners working with the primary healthcare sector in Gauteng province, South Africa, were asked to complete the administered questionnaires. These questionnaires were administered to the respondents through the WhatsApp handle platform. About 420 questionnaires were retrieved and 400 were used while twenty were rejected because of inconsistencies in the responses. The analysis represents 56% and 53% return and response rates, respectively (Bougie & Sekaran, 2019).

The main instrument for this research was an online administered questionnaire, and the questionnaire contains only closed-ended questions (Kock, 2017). The adapted questions used in the questionnaire were captured by four (4) study constructs of smart healthcare building facilities related factors (SMAHEAL), as a dependent variable and IoT Location Recognition and Tracking Services (IoT-LORE), IoT High-Speed Communication Network-Based Services (IoT-HISB), and IoT-Based Services (IoT-BAS) were the independent variables, respectively. All the constructs used were measured using a 5-point Likert scale. Through the development of a model. The partial least squares structural equation modelling (PLS-SEM) was used for data analysis.

Hair et al. (2019) suggested that the PLS-SEM software is used to enable the building of theories through the establishment of causal relationships among the study constructs. Contrarily, covariance-based structural equation modelling (CB-SEM), is commonly used to confirm relationships and theories among constructs (Hair et al., 2019). Furthermore, PLS-SEM software is used for data analysis due to its high predictive capability and it is used to assess the validity of the constructs measured (Hair et al., 2019). The measurement model of this study was shown in Figure 1. This indicated the number of items in each

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study construct. Similarly, Table 1 shows the sources from which the items of each construct were adapted.

2.1. Theoretical Frameworks

This study adopted two (2) theories: the Scientific Management Theory and Schumpeter's Innovation Theory. The two (2) theories tend to explain the relationship between the application and use of technology in minimising the causal effect of variables. i.e., the application of technology such as IoT services to achieve enhanced building facilities services at the primary healthcare units for healthcare delivery services.

The scientific management theory was developed by Frederick Taylor (2004), which posits that scientific and technological methods should be used to perform tasks in the workplace, as opposed to the leaders relying on their judgment or the personal discretion of team members. This theory was adopted because the theory explains that scientific and technological methods like the application of IoT services towards enhancing smart building facility services would result in the most productive workplace.

While Schumpeter's Theory of Innovation (1939) is in line with other business investment theories, which assert that the change in business investment accompanied by monetary expansion is the major factor behind the business improvement, Schumpeter's Theory posits that business innovation is the major reason for enhancing service delivery, hence improving productivity in investments and business success. The two theories explained the relationship between study constructs. Accordingly, the theories advocate the adoption of technology to enhance service delivery in the healthcare building facility.

Table 1. the sources of items in the study constructs.

	Khan & Salah, (2018)	Wassie et al., (2022)	Kwon et al., (2022)	Birje & Hanji, (2020)	Verdejo et al., (2021)	Schuchat et al., 2020	(Zhao & Jiang, 2018	Yan (2019)	Singh & Mahapatra, 2020	(Karthick et al., (2022)	Jackson (2002)	de la Torre Díez et al., (2019)	Kang (2019)
SMAHEAL													
Interoperability of the building facilities	√		√										
Mobile integrated solution		√	√										
Digitisation of information		√											
A unified system of communication system		√	√										
Stable core infrastructure facilities	√		√										
System automation	√		√										
IoT-LORETS													
Beacons Technologies		√		√	√	√							
Bluetooth Technologies				√									
Wi-Fi Technologies				√	√								
Zigbee Technologies				√		√							
RFID Technologies			√										
GPS and A-GPS Technologies			√		√								
Barcodes and QR codes			√			√							
Ultra-wideband communication			√		√	√							
IoT-HISBAS													
Integrating IoT into 5G and B5G high-speed								√	√				

	Khan & Salah, (2018)	Wassie et al., (2022)	Kwon et al., (2022)	Birje & Hanji, (2020)	Verdejo et al., (2021)	Schuchat et al., 2020	(Zhao & Jiang, 2018	Yan (2019)	Singh & Mahapatra, 2020	(Karthick et al., (2022)	Jackson (2002)	de la Torre Díez et al., (2019)	Kang (2019)
communication													
Wi-Fi 6						√			√				
OFDMA technology					√			√					
infusion pump							√		√				
Sensors and wearables for IoT-based wireless health						√			√				
Facility-to-facility connectivity with high mobility					√		√	√					
IoT-BAS													
Facilities identification										√		√	√
Network construction										√	√	√	
Sensor attachment										√			√
Sensor control											√	√	
Cloud computing and analytics										√	√		√

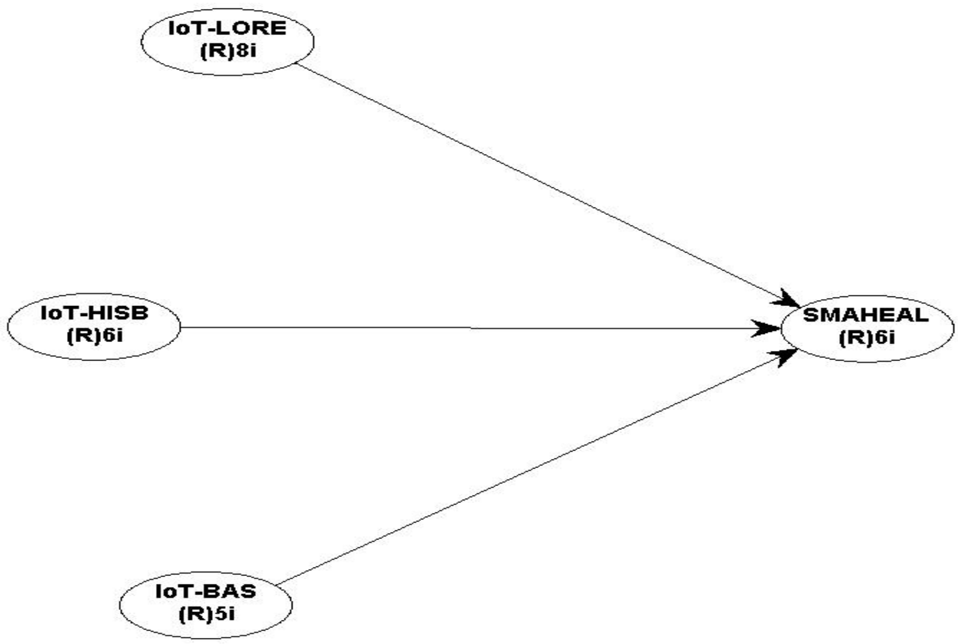

Figure 1. Measurement Model.

The research constructs cover the IoT service factors that enable the achievement of smart primary healthcare building facility services. The IoT services comprise three (3) constructs namely, IoT-LORE, IoT-HIBS, and IoT-BAS, while the dependent variable was Smart primary healthcare building facility SMAHEAL. All four constructs, i.e., dependent and independents were rated by a 5-point Likert scale. This scale concerns uni-dimensionality and is the utmost and most common scaling process used in engineering management research (Hair et al., 2014). The operationalisation of the independent variables was achieved by rating the scales from the very low rating – the very high impact rating. In contrast, the dependent variable was the very low rating – the very high level of smartness rating of the healthcare facility. The operationalisation process was adapted from Gambo & Musonda's (2021) studies. The data was collected by online administered questionnaires that were retrieved unanalysed using PLS-SEM algorithms.

According to the measurement model presented in figure 1. The following directional alternate hypotheses were developed:

H_{A1}: There is a significant positive impact between the application of IoT location recognition and tracking services and the achievement of smart primary healthcare building facilities

H_{A2}: There is a significant positive impact between the application of IoT high-speed communication network-based services and the achievement of smart primary healthcare building facilities

H_{A3}: There is a significant positive impact between the application of IoT-based services and the achievement of smart primary healthcare building facilities. 3 Results

3. Results

3.1. Respondents' demographic information

Table 2 indicates the demography of the respondent groups. The respondent group comprises experienced project managers and healthcare practitioners working with the public sector in Gauteng, South Africa. The statistics indicate that about 51.75% of the respondents were project managers, while the remaining 48.27% were primary healthcare practitioners. The results further showed that 10.00% were PhD holders, 40.25% were M.Sc. holders and the remaining 49.75% were BSc holders. The average working experience of the respondents was approximately thirteen (13) years, indicating that the respondents were experienced enough with primary healthcare building provision.

Table 2. Information on Respondents' Demography.

Project Managers	**No.**	**%**	**Cumulative %**	
Project Managers	207	51.75	51.75	
Healthcare Practitioners	193	48.25	100	
Total	**400**	**100**		
Educational Qualifications				
PhD	40	10.00	10.00	
MSc	161	40.25	50.25	
BSc	199	49.75	100	
Total	**400**	**100**		
Experience of Respondents (Year)				
Years	**Mid Value (x)**	**Frequency (f)**	**% of Frequency**	**Fx**
5-10	7.5	85	21.25	637.50
10-15	12.5	109	27.25	1362.50
15 and above	15.0	206	51.50	3090.00
Total		**400**	**100**	**5090.00**

Calculated Mean (average) years of working experience of the respondents $\Sigma fx/\Sigma f = 5090.00/400 = 12.73 \approx 13$ mean years of working experience

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3.2. Indicators of the model fits

Past studies focused on some essential sets of guidelines for manuscript reports that have confirmatory factor analysis (CFA) as the primary statistical analysis technique. The statistical indicators include the followings: Alike Information Criteria and the Chi-square (χ^2), Parsimonious fit, Comparative fit, Goodness-of-fit index, Standardized root mean square residual (SRMR), and Root means square error (RMSE), Bentler-Bonett or Normed fit index (Hair *et al*., 2019).

Though, Kock (2017) differentiated that there is a philosophically forthright distinction between the CB-SEM and the PLS-SEM that this study used based on the objective of the study. Suppose the research objective is intended for theory development, testing and confirmation. In that case, the best method is to use the CB-SEM. Still, in contrast, when the research objective is the prediction and development of theories, then the best method is to use the PLS-SEM approach. Therefore, the present study entails theory development and prediction. Conceptually, PLS-SEM is similar to multiple regression analysis of data.

Based on the interpretations of the model fits, when the target of the research is to test the developed hypotheses, wherever each arrow in the conceptual model signifies a hypothesis, then the fit indices are less important. But, if the intention is to assess how the collated data fit into the developed model. Then the model fits indices are vital indicators associated with the quality of the model (Kock, 2017).

However, the Warp PLS-SEM algorithms indicated the following indices which compare the indicators of the correlation matrices that include: the standardised mean absolute residual (SMAR), standardised root means squared residual (SRMR), standardised chi-squared (SChS), standardised threshold difference count ratio (STDCR), and the standardised threshold difference sum ratio (STDSR). However, some classic model fits, and the explanation of the indices depends on the aim of the study. Subsequently, the indices denote the fits between the empirical indicator correlation matrices and model-implied. The indices become more expressive when the aim is to assess whether the model fits better with the collated data than the other, mainly when used together with the common indices (Kock, 2017).

An analysis of the model fits indicated the following statistics such as the average path coefficient (APC) was 0.308, which was significant with $_{\text{a P-value}} < 0.001$, the Average R-squared had a statistics value of 0.635 with a $P_{\text{-value}} < 0.001$, and the Average Adjusted R-squared (AARS) was having a statistical value of 0.632 with a $P_{\text{-value-value}} < 0.001$. The statistics of Average Block VIF (AVIF) was 1.686, which is regarded as acceptable if it is <= 5; ideally, if it is <= 3.3, therefore the AVIF in this model is regarded as an ideal. The Average Full Collinearity VIF (AFVIF) has a statistical value of 2.090, regarded as acceptable if it is <= 5; ideally, if it is <= 3.3, therefore the AFVIF in this model was regarded as an ideal. The VIF measures are used when indicators are formative.

The model fits also indicated that the Tenenhaus GoF (GoF) has a statistical index of 0.522, regarded as small if it is >= 0.1, medium if it is >= 0.25, and large if is >= 0.36, therefore the GoF here is regarded as significant, The GoF is the geometric average of the commonality. The average R^2 of endogenous variables signifies the index for validating the PLS model. Generally, it is a compromise between the performance of the instrument and the structural model developed.

The results further indicate that the Simpson's paradox ratio (SPR) had a statistic of 1.000 regarded as acceptable if it is greater or equals 0.7, and ideally if it is 1.00. Therefore, SPR in this model is ideally. The R-Squared Contribution Ratio (RSCR) has a statistic of 1.000, regarded as acceptable if it is >= 0.9. Ideally, if it is = 1, therefore, the RSCR of this model was regarded as an ideal. The Statistical Suppression Ratio (SSR) had a statistical value of 1.000, which was considered acceptable if it is greater or equal to 0.7; therefore, it is acceptable in this model. The nonlinear bivariate causality direction ratio (NLBCDR) had a statistical value of 1.000, regarded as acceptable if it is greater or equal to 0.7, therefore is seen as acceptable. Hence based on the above statistical indices, this model is considered to have good fit indices (Kock, 2017).

3.3. Measurement Model

Table 2 indicates an assessment of the model, which commonly follows two stages: the evaluation of the measurement and the structural model parameters (Hair et al., 2019). The measurement model estimates inspect the instrument's validity and reliability including the correlations among the indicators. Thus, the model had four (4) constructs: SMA-HEAL, IoT-LORE, IoT-HIBS, and IoT-BAS.

The measurement model appraises the model's reliability and validity which the following two criteria: composite reliability (CR) and the average variance extracted (AVE) (Hair et al., 2019). Moreover, the study earlier involved internal consistency to test the reliability of the instrument. According to Benjamin et al. (2018), Cronbach's alpha (α) tests the consistencies of the questionnaire and the level of the random error. Using Cronbach's alpha allows quick detection of negative factors and then removal. While the positive is accepted that ranging from a scale of 0.0 to 1.0 (Hair et al., 2019). The minimum suitable value of Cronbach's alpha is 0.6 (Ho, 2006). Once an item is used as a scale, the item is required to be within the benchmark (0.60 and above) for the values of the reliability indicators. Ho (2006) stated that the reliability of an instrument is defined as its capability of the instrument to quantity the circumstance it is intended to measure steadily.

Construct reliability refers to test consistency. The significance of reliability is within the fact that it is a precondition for the validity of the study instrument. The consistency test encompasses the item analysis, split-half technique, and Cronbach's alpha method. The main inadequacy of Cronbach's alpha test is that it under-estimates the consistency of a variable having small sample sizes of less than a hundred (100) units. Still, a construct with a large sample size of more than a hundred (100) units. The Cronbach alpha is employed to examine the internal consistency of variables (Hair et al., 2019). Moreover, Ho (2006) suggested Cronbach's alpha test as dependable among others. The Cronbach's alpha test delivers an exclusive estimation of a scale's internal consistency.

Consequently, the study indicators and construct reliability are examined to appraise the consistencies of the measurement model. Two tests are used to assess the reliability of the construct, i.e., the CR and Cronbach's alpha tests. Hair et al. (2019) suggested CR for PLS-SEM software. On the other hand, the validity was assessed by double-checking the loading of the indicator on its related construct, and the loading should be from 0.70 and higher before accepting the validity of the indicator (Hair et al., 2019).

Table 3 shows the results of the measurement model. The results indicated high validity and internal consistency among the indicators in the model. All the factor loadings were all greater than the benchmark of 0.70. Whereas the CR and Cronbach's oscillated from 0.702 to 0.846 and 0.718 to 0.775, respectively. This shows that all the indicators and the reliabilities adequate. The discriminant and convergent validities were also considered in the validation of the measurement model. The AVE values of the constructs should be from 0.50 and higher for a recognized convergent validity test (Hair et al., 2019). The AVE is used only for models having reflective indicator variables. The AVE assesses the entire variance of a construct over its indicators (Ho, 2006). The AVE figures of this model oscillated from 0.500 to 0.585, indicating that were within the acceptable benchmark of 0.500. Hence, indicating the acceptability of the convergent validity of the instrument.

Table 3. Assessment of the study measurement.

Construct	Indicators	Indicator Loading	CR	Cronbach's α	AVE
SMAHEAL	SMAHEAL1	0.832	0.846	0.775	0.500
	SMAHEAL2	0.824			
	SMAHEAL3	0.754			
	SMAHEAL4	0.856			
	SMAHEAL5	0.275			
	SMAHEAL6	0.719			
IoT-LORE	IoT-LORE1	0.793	0.702	0.730	0.524
	IoT-LORE2	0.870			
	IoT-LORE3	0.873			
	IoT-LORE4	0.768			
	IoT-LORE5	0.784			
	IoT-LORE6	0.774			
	IoT-LORE7	0.726			
	IoT-LORE8	0.733			
IoT-HISB	IoT-HISB1	0.759	0.753	0.718	0.585
	IoT-HISB2	0.768			
	IoT-HISB3	0.768			
	IoT-HISB4	0.761			
	IoT-HISB5	0.730			
	IoT-HISB6	0.721			
IoT-BAS	IoT-BAS1	0.769	0.837	0.756	0.508
	IoT-BAS2	0.795			
	IoT-BAS3	0.725			
	IoT-BAS4	0.795			
	IoT-BAS5	0.770			

Note: α-alpha; CR-composite reliability; AVE- average variance extracted

Table 4 shows the measurement model's discriminant validity. The validity is the degree to which the construct is distinguished from other constructs in the model. This is attained by double-checking the AVE of the construct which must be greater than the largest squared correlation of the construct. Alternatively, the loading of the construct must be greater than the other constructs in the model (Hair *et al.*, 2019). These results showed that the square root of AVE for the construct with its relationship with another is an acceptable discriminant validity. Based on the results above the questionnaire was regarded as valid and reliable for the intended purpose.

Table 4. Results for discriminant validity.

	SMAHEAL	IoT-LORE	IoT-HISB	IoT-BAS
SMAHEAL	**0.707**			
IoT-LORE	0.133	**0.570**		
IoT-HISB	0.656	**0.018**	**0.620**	
IoT-BAS	0.701	0.098	0.621	**0.712**

Note: Discriminant validity showing AVE

3.4. The Measures of the Path Coefficients of the Developed Model

Figure 2 indicated the coefficient of determination (R^2) as the measure of the endogenous variables and the path coefficients of the developed model. This is appraised as a component of an initial evaluation of the structural relationships, i.e., the inner developed model from the conceptual/hypothetical framework of this study (Hair et al. 2019). Thus, Chin (1998) suggested the figure of 0.67 for substantial, a figure of 0.33 for moderate, and a figure of 0.19 for weak values of R^2. The value of R^2 here was 0.635, indicating a significant and moderate relationship occurred between criterion (IoT-Services) and predictor variables (SMAHEAL). The path coefficients between IoT-LORE, IoT-HABS, IoT-BAS and the dependent variable SMAHEAL were 0.090, 0.265, and 0.570, all significant at a $P_{0.05}$ level, respectively.

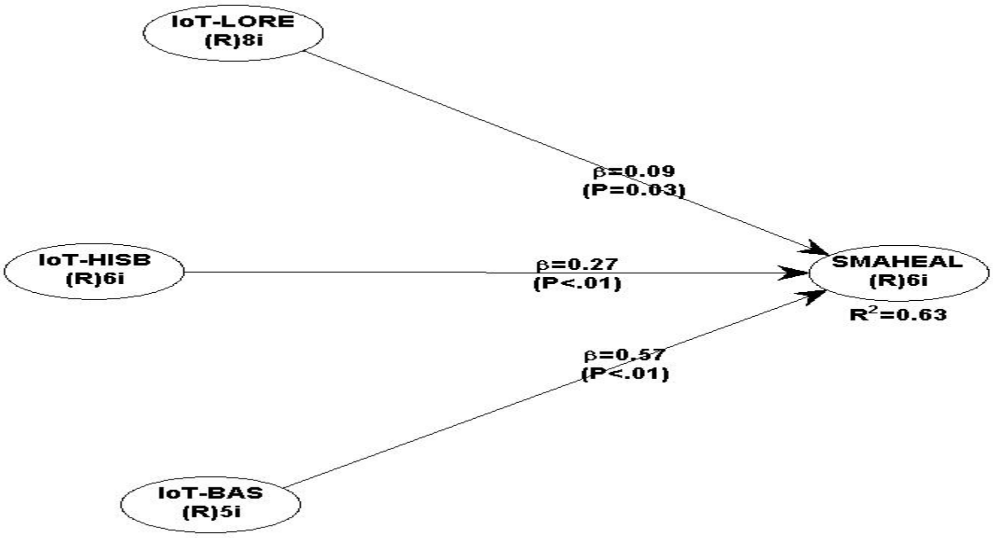

Figure 2. Structural Model of the Constructs.

Table 5 indicates the effect sizes (f^2) as a figure to confirm whether the impact of one independent variable on the dependent variable forecasted by the path coefficients was either low for the value of 0.02, moderate for the value of 0.15, or high for the values of 0.35 (Cohen, 1988). The value of f^2 shows the impact of a specific construct on the dependent variable is considerable (Chin 2010). The value of f^2 between IoT-LORE, IoT-HIBS, IoT-BAS, and the dependent variable SMAHEAL were 0.018, 0.178, and 0.439 indicating low, moderate, and high, respectively. Similarly, the predictive capability of the endogenous constructs in the relationship was assessed using Stone-Geisser's cross-validated redundancy (Q^2). The predictive ability for the relationship was 0.635, and the software automatically generates the figure for the Q^2 (Kock, 2017). But, Hair et *al.* (2019) described that Q^2 values show the predictive significance as either weak for the value of 0.02, moderate for the value of 0.15, and strong for the value of 0.35, figures. Consequently, this model shows robust predictive significance because $Q^2 > 0$, i.e., 0.635 precisely. Therefore, the path model's predictive significance to the construct is strong. This implies that the predictors (IoT-LORE, IoT-HIBS, IoT-BAS) predict about 64% achievement of SMAHEAL whenever adopted.

Table 5. Testing of the Study Hypotheses.

Hypotheses	Path coefficient	P-value	Effect size (f^2)	Stone-Geisser's Q^2	R^2	Supported
IoT-LORE→SMAHEAL	0.090	0.035	0.018			Yes
IoT-HIBS→SMAHEAL	0.265	<0.001	0.178	0.635	0.635	Yes
IoT-BAS→SMAHEAL	0.570	<0.001	0.439			Yes

Note: Level of significance (p) ≤ 0.05; Q^2-cross-validated redundancy

4. Discussion of Results

This study assessed the impacts of IoT services on achieving smart primary healthcare building facilities. The study comprises four (4) constructs: SMAHEAL (dependent variable), IoT-LORE, IoT- HIBS, and I0T-BAS. The constructs were adapted from previous studies in IoT and smart healthcare buildings.

The study measurement model indicates that the research instrument is highly reliable and valid for the intended purpose. Hence, demonstrating the reliability and validity of the results. The study found significant variable impacts between the IoT services (IoT-LORE, IoT-HIBS, and the IoT-BAS) and the SMAHEAL. The impact between the SMAHEAL and the IoT-LORE indicates a significant and low impact (0.018) relationship exists between the two constructs (Cohen, 1988). This supported the hypothesis, indicating a significant positive impact between the application of IoT location recognition and tracking services and the achievement of smart primary healthcare building facility services. The result is in line with the findings of Jia et al. (2019), who studies the need for the adoption of IoT for the development of smart buildings, which also indicates a small relationship between the IoT location recognition and tracking services for the smart infrastructure. However, the study contradicts the findings of Bagheri and Movahed (2016) on the effect of IoT on the education business model, which found a moderate relationship. This is because the study considered general learning and educational environments without infrastructure facilities.

Similarly, the results showed that there is a significant and moderate impact (0.178) between the IoT- HIBS and the SMAHEAL (Cohen, 1988), which hence supported the hypothesis that there is a significant positive impact between the application of IoT high-speed communication network-based services and the achievement of smart primary healthcare building facility services. This is in line with Ramesh et al. (2020), which evaluates the achievement of sustainability through smart city applications: protocols, systems and solutions using IoT and wireless sensor networks and found a moderate relationship between sustainable smart cities and high-speed communication networks protocols. On the other hand, the study contradicts that of Ahad et al. (2020), which assessed the technological trend toward 5G networks for smart health care using IoT because the study considers only one indicator of IoT-HIBS, i.e., 5G Networks.

Lastly, the results also indicated a high impact (0.439) between the IoT-BAS and the SMAHEAL Cohen, (1988), which also supported the hypothesis that there is a significant positive impact between the application of IoT-based services and the achievement of smart primary healthcare building facility services. This is also in line with the study of Lawal and Rafsanjani (2021), which assessed the trends, benefits, risks, and challenges of IoT implementation in residential and commercial buildings and concluded that IoT-based services significantly improve the smartness of building infrastructure. Contrarily, the results of this study oppose that of Jia et al. (2019), who studies the adoption of IoT for the development of smart buildings and found a weak relationship between the IoT-based services and the development of smart cities.

5. Conclusion

The study aims to assess the impact of IoT services (IoT-LORE, IoT-HIBS, and IoT-BAS) towards achieving smart primary healthcare building facility services (SMAHEAL). With the view to improve the delivery of primary healthcare building facility services in developing countries. The study identified three (3) basic constructs of IoT services comprised of the application of IoT location recognition and tracking services (IoT-LORE), the application of IoT high-speed communication network-based services (IoT-HIBS), and the application of IoT-based services (IoT-BAS) that help in achieving smart primary healthcare building facility services for rapid healthcare delivery in the rural areas of developing countries.

The results found that there are variable impacts between the three (3) IoT services and achieving smart primary healthcare building facility services, which indicate both low, moderate, and high impact changes for IoT-LORE, IoT-HIBS, and IoT-BAS with the SMAHEAL, respectively. This implies that positive variable degrees of influence exists between the independents and the dependent variable. Impliedly, the application of IoT services positively and variable aid in achieving smartness of primary healthcare building facility services for an enhanced primary healthcare service delivery in developing countries.

Therefore, the study recommends adopting IoT services towards achieving primary healthcare services in the rural areas of South Africa and other developing countries with similar challenges of primary healthcare building facility services in South Africa. Consequently, the study recommends further and continuous studies on adopting IoT services for achieving smart primary healthcare services to fully realise the potential that the technologies offer for rural communities.

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