Data Input, Data Processing Practices and Service Delivery of Health Information Personnel in Tertiary Hospitals in Owerri, Imo State, Nigeria

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Abstract

Effectiveness of health information professionals has a lot of link with their service delivery level. A major factor that has been identified that will always boost the service delivery of health information professionals is the way and manner data is being processed. Deficiencies in data processing practices will results in questionable service delivery of health information professionals. It is in this regard that this study deemed it fit to investigate the influence of data processing practices on service delivery of health information professionals in tertiary institutions in Owerri, Imo state. The survey design was used. The targeted population consisted of 118 respondents sampled randomly from health information professionals in tertiary institutions in Owerri, Imo state. Total enumeration sampling technique was used. A validated questionnaire with reliability coefficient of 0.74 was used as the instrument for data collection. Response rate was 97.4%. The data were analyzed using descriptive and regression statistics. The study revealed that three out of the four component data processing practices (data input and data processing) significantly influenced service delivery ((R^2 = 0.001; P >.05). The study recommended in the wake of the obstructive nature of technological innovations, For Health Information Professionals, there should be laid down rule regarding training and retraining so as to keep up with the pace.

Keywords: Data processing practices**,** Health information professionals**,** Service delivery.

Word Count: 203

Introduction

The service delivery of health information personnel in tertiary institutions plays a crucial role in ensuring the effective management and dissemination of health-related information within the academic community (Hamad, Al-Fadel, & Fakhouri, 2022). To start with, health information personnel are responsible for organizing and delivering health education programs and campaigns within the institution. This may include workshops, seminars, and awareness campaigns on topics such as nutrition, exercise, mental health, sexual health, and disease prevention.They manage health information resources such as books, journals, databases, and online resources, ensuring that students and faculty have access to up-to-date and reliable information for research and academic purposes. They oversee the maintenance and management of medical records for students and staff. This includes ensuring the confidentiality, accuracy, and accessibility of health records in compliance with relevant regulations and standards.They collect, analyze, and interpret health data to identify trends, patterns, and areas for improvement in the areas of health. In some cases, health information personnel may provide support services within clinical settings, such as hospitals or student health centers. This may involve managing electronic health records, coding diagnoses and procedures for reimbursement purposes, and ensuring the accuracy and completeness of patient records. Moreover, with the increasing use of technology in healthcare, health information personnel play a crucial role in integrating new technologies into existing systems. This may include implementing electronic health record systems, developing health information websites or apps, and training staff on the use of new technologies (Ma, Stahl, & Price, 2020; Al Kiyumi, Walker, Tariq, & Fitzgerald, 2016).

As the usage of information and communication technology continues to rise, hospitals and their patients can benefit from electronic service delivery to save money and time. The quality of a service is measured by how well it meets customers' needs. Health information professionals' contributions to patient care will be evaluated using a modified version of the dimensions of service intangibility, ideology, variability, and constraints developed in the context of Human Service Delivery Theory (Austin & Carnochan, 2020).

The healthcare industry relies heavily on data. The entry of data is a crucial step towards making well-informed choices. Elements of data will be used for strategic patient care and ongoing quality improvement within a healthcare facility. Also, comparing different programs aimed at improving public health. Filling out forms, tally sheets, and registers, feeding data into aggregated reports and statistics, and reporting health data from lower levels to higher levels are all examples of working with data and information inside the health information system. Most health information workers spend significant time performing these duties. Because of this, health information systems are rarely seen as separate from the social framework of which they are a part (Woolf, Chan, Harris, Sheridan, Braddock, Kaplan & Tunis, 2005). Data, because of its importance and inevitable roles it plays in decision making must be accurate, reliable, and organized so that it can be understood and health information can be retrieved, whether it is being input into a paper medical/health record, a computer-based or electronic patient record, for statistics, or specific registries (Provost, & Fawcett, 2013). The first thing to do is figure out what kind of data is required and how it will be collected. Data processing practice generally is made up of different aspects as well as stages which includes data processing, data input, data storage, data output and data usage(Heip, Herman, & Soetaert, 1981). This study focuses on two aspect of data processing which are data input and data storage. Data input state connotes data collection practice, data capture practice, data transmission practice, data communication practice. The second stage which data storage connotesthe duo of performing instructions and transform raw data into information(Emetere, Akinlabi, Emetere, & Akinlabi, 2020).

Data storage refers to a repository for information that may be accessed and used to inform and guide managerial decision-making in a variety of contexts and over time. There is specific business information stored in the repository. When it comes to hospital applications, classical operations systems are subject-oriented. When it comes to integration, the data storage receives input from a wide variety of unrelated sources. Data is transformed, processed, rearranged, and summarized as it is continuously supplied in. This means that once data is stored, it has a unified physical representation across all locations. Information from storage is read and used, but not modified. Instead, a snapshot, static format is used to load data from the storage. A new snapshot record is created if there are subsequent changes. This creates a log of past records in the database. The ability to store and retrieve information has been heralded as a game-changing advancement in the field of information technology. This is due, in part, to the fact that it is thought of as a solution to the problem of too much data(Mosweu, 2019).

With the explosion of digital information and the pressing need to put that information to work in ways outside the scope of mundane, day-to-day processing, data storage has emerged as a distinct industry. Senior management of a big hospital system with multiple locations typically need to measure and analyze the contributions of each location to the system's overall success. Information about the various corporate departments' respective workloads can be found in the company's central database. Customized queries can be issued to retrieve the necessary information to fulfill the managers' needs. The initial step in this procedure is for health information professionals to carefully examine database catalogs in order to build the appropriate query. The query is then answered. Due to the massive volume of data, the intricacy of the query, and the impact of other normal workload queries on the data, this can take many hours. At last, a spreadsheet report is made and given to upper management. Database designers long ago acknowledged that such a method is highly impractical since it is so time- and resource-intensive, and because it does not always produce the desired results. However, modern data warehousing processes decouple analytical and transactional online processing by building a new data repository that consolidates data from multiple sources, sorts it into useful formats, and makes it accessible for analysis and evaluation in support of planning and decision-making (Amollo, 2021).

Clinical and administrative leaders integrated electronic health record adoption into their strategic plans to integrate inpatient and outpatient care and provide a continuum of coordinated services, according to a study of hospitals that recently implemented a comprehensive electronic health record system (Amollo, 2021). Strong leadership, complete participation of clinical personnel in design and implementation, mandated staff training, and tight adherence to time and budget were all required for a successful rollout. Through the use of checklists, alerts, and predictive tools; embedded clinical guidelines that promote standard, evidence-based practices; electronic prescribing and test-ordering that reduces errors and redundancy; and discrete data fields that foster use of performance dashboards and compliance reports, electronic health record systems promote patient safety and quality improvement. Improved patient flow, less duplicate tests, quicker replies to patient concerns, redeployment of transcribing and claims employees, more thorough collection of charges, and federal incentive payments are all results of better communication and optimized operations (Amollo, 2021).

Overall, effective data input and storage practices could be an essential integral part of data processing liable of ensuring the accuracy, timeliness, integrity, security, accessibility, and interoperability of health information, ultimately influencing the quality and efficiency of service delivery among health information professionals in tertiary institutions. Looking at the intricate roles of this two aspects of data management to healthcare delivery, the study aimed at finding out the data input and processing practices as it relates to the quality of healthcare delivered in universities hospitals in Owerri, Imo State, Nigeria.

Close observation has found deficient service delivery among health information personnels and this could be as a result of laxities observed in data processing practices.This could have adverse effects on tertiary hospitals' decision making, healthcare delivery, performance and a decline in reputation of the hospitals. This prompted this study to fill in the gap to provide information on data processing practices (data input and data storage) and service delivery of health information personnel in Tertiary Hospitals in Owerri, Imo State, Nigeria.

Research Questions

1. What is the level of Service Delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria?

2. What are the data processing practices adopted by health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria?

Hypothesis

The study came up with two null hypothesis all measured at 0.05 level of significance

1. There is no significant influence of data input on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria.

2. There is no significant influence of data processing on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria.

Literature review

Implementing accurate data management systems ensure safe and efficient transfer of confidential health care data. However, health care professionals overlooked their important tasks of medical data processing. Hence, using high-quality electronic health record (EHR) applications in health care is important to minimize medical errors (Adane, Gizachew & Kendie, 2019). More so, in the growth of scientific medicine, medical records have played an important role as a tool and basis for planning patient care besides medical education, research and legal protection (Mogli, 2009). According to Urooj, Nafis, & Ahmad, (2021). Any time health information staff interacts with a patient's health records in order to update or correct them so that those records can be used by healthcare providers for the benefit of patients is considered service delivery. These services must be provided in a way that is efficient, consistent, and meets the needs of the patients receiving them. As the usage of information and communication technology continues to rise, hospitals and their patients can benefit from electronic service delivery to save money and time. The quality of a service is measured by how well it meets customers' needs. Based on the literature, we will evaluate health information staff based on their ability to make data available, maintain data consistency, and ensure data accuracy.

According to assertions by Usak, Kubiatko, Shabbir, Viktorovna Dudnik, Jermsittiparsert, &Rajabion, (2020), Service delivery is an integral part of health system where patients receive the treatment and supplies they are entitled to all the other parts of the health system examined in this part support the delivery of healthcare services and as a result. A health data system is a functional entity within the framework of a comprehensive health system to improve the health of individuals and the population. As such, it is a management information system. The health data structure should allow generation of necessary information for use in decision-making at each level of the health system with a given amount of resources. This involves the processes for collecting, processing and disseminating information in a health system (World Health Organization, 2020).

Information for a data warehouse comes from both internal and external sources, including the likes of the company's suppliers and regulatory bodies. The data must be retrieved from the original systems, cleaned, and changed so that it fits the standard architecture before being fed into the data warehouse. This process, often known as ETL (Extract, Transformation, and Load), is crucial to every data warehouse. Metadata, which includes data models, a data dictionary, and ETL load statistics, is another crucial component that must be established and made easily accessible to the user community in order for the data warehouse to function effectively (Nath, Romero, Pedersen, & Hose, 2020).

A consistent and logical process must be followed by the data as it moves through the data storage system in order for the information to be displayed to users in a manner that is uniform and consistent. The dimensional approach stores data in a form similar to both its true dimensionality and the form needed at the time of reporting. The relational approach, which relies on relational database management principles, stores data in a form similar to both its true dimensionality and the form needed at the time of reporting (Emetere, Akinlabi, Emetere, & Akinlabi, 2020). The storage of the data usually follows the relational approach rather than the dimensional approach. A multidimensional perspective of the data, such as by service or location as well as over time, can be obtained by drawing smaller subsets of data from the data warehouse and storing them in databases that have been developed specifically for that purpose. This helps to better meet the requirements of individual users. These subsets make it possible to have a deeper knowledge of the data, to investigate them further, and to provide faster responses to queries(Boussaid, Tanasescu, Bentayeb, & Darmont, 2007).

Electronic Health Records (EHRs) have the potential to improve patient care in hospitals, but their widespread adoption has been slowed by a number of factors. Some of these issues include a shortage of available IT specialists, insufficient funds for initial investment and ongoing maintenance, resistance from doctors, and a murky return on investment. Four of these five concerns were less frequently cited as important hurdles to adoption by hospitals that had already embraced electronic records systems, compared to hospitals that had not. Despite the widespread belief that technological advancements can improve medical treatment, there is a paucity of data to back up this claim. In practice, many choices about implementing new health care technologies are made without enough knowledge of their potential consequences. When it comes to the efficacy, costs, ethics, legal, or social repercussions of technology, decision-makers rarely receive feedback on the consequences of their actions since they are often unaware of the knowledge they lack (Spatar, Kok, Basoglu, & Daim, 2019).

With the goal of aiding in decision-making during classification tasks, a researcher developed a sophisticated system for autonomously classifying brain MRI pictures of neurodegenerative illnesses. On a large database (more than 1,500 patients were evaluated), the approach showed a sensitivity and specificity of 90%, both of which are significantly higher than those anticipated by human experts(Kusakunniran, Karnjanapreechakorn, Siriapisith, Borwarnginn, Sutassananon, Tongdee, &Saiviroonporn, 2021).

By analyzing consumer search, social content, and query activity, BDA (British Dietetic Association) offers a novel approach to the problem of predicting disease outbreaks in the public health sector. To better understand illness patterns and ensure the safety of medications, public health systems also aid doctors and epidemiologists in conducting analyses including a wide range of patients and treatment settings. The use of BDA in disease network surveillance is widespread. Google, for instance, employs BDA to analyze search-engine query patterns in order to foresee the spread of disease. About a third of Internet users (those who use Facebook, YouTube, blogs, Google, or Twitter) are already using these services to get health-related information. As the need for health data from SNSs grows, BDA has the potential to bolster vital disease-prevention initiatives like surveillance and outbreak control (Corsi, de Souza, Pagani, & Kovaleski, 2021). The Global Burden of Disease Study (GBD) evaluates mortality and disability due to major diseases, injuries, and risk factors on a regional and global scale. More than 1,800 researchers from about 195 countries, most were involved in GBD, which uses medical Big Data(Safiri, Sepanlou, Ikuta, Bisignano, Salimzadeh, Delavari, & Mirzaei, 2019). All these data by various organizations and bodies can aid quick and quality decisions regarding healthcare delivery thereby fostering professionalism of health information personnels in the discharge of their duties.

Methodology

The survey design was used. The target population consisted of 118 respondents sampled randomly from health information professionals in tertiary institutions in Owerri, Imo state. Total enumeration sampling technique served as the sampling technique used in this study. A validated questionnaire was the instrument used for data collection. Reliability coefficient of each of the variables ranged from 0.74 to 0.89. Response rate was 97.4%. The data were analyzed using descriptive and regression statistics.

Analysis

The analysis showed that record of 61 female respondents which account for about 51.7% and 57 male respondents which account for about 48.3%. Considering the age range, 40.7% of the respondents fall within the age range of 31 to 40 years of age. 13. 6% of the respondents are within the age range of 20 to 30 years of age. 26.3% of the respondents accounted for about 41 to 50 years of age while only 23 respondents are 51 years of age and above. Those that have a master's degree accounted for about 26.3%s percent of the total population, while 52.5% accounted for those who claim to have just a bachelor's degree and Higher National Diploma.

Table 1: Level of Service Delivery of Health Information Personnel

Items	SA	A	D	SD	M
Service Intangibility					
My place of work has state-of-the-art facilities to help health information professionals discharge their duties effectively.	23 (19.5%)	27 (22.9%)	30 (25.4%)	38 (32.2%)	2.3
ICT facilities in my place of work available for health information professionals to work with are working efficiently and	40 (33.9%)	27 (22.9%)	38 (22.9%)	13 (11.0%)	2.8

effectively.					
Patients' electronic health record in my place of work are well secured.	36 (30.5%)	17 (14.4%)	40 (33.9%)	25 (21.2%)	2.54
Average Mean: 2.54					
Service Ideology					
Participation in service learning activities in my place of work helped me to better understand lecture and reading materials.	10 (8.5%)	21 (17.8%)	48 (40.7%)	39 (33.1%)	2.02
My service learning experience in my place of work so far has directly influenced my record handling skills.	1 (.8%)	23 (19.5%)	58 (49.2%)	36 (30.5%)	1.91
I never encountered any difficulty all through my service learning experience.	14 (11.9%)	23 (19.5%)	54 (45.8%)	27 (22.9%)	2.20
Average Mean: 2.04					
Service Variability					
Patients' records are positively handled through my data handling ability	0 (0%)	0 (0%)	57 (48.3%)	61 (51.7%)	1.48
Patients' record issues are positive dealt with in my place of work.	23 (19.5%)	31 (26.3%)	48 (40.7%)	16 (13.6%)	2.52
My place of work is very much conducive for the handling of patients' records.	6 (5.1%)	31 (26.3%)	62 (52.5%)	19 (16.1%)	2.20
Average Mean: 2.06					
Service Limits					
Information about patients in my place of work by myself and colleagues is well written in easy to read language.	10 (8.5%)	26 (22.0%)	54 (45.8%)	28 (23.7%)	2.15
My colleagues and me do communicate effectively well with patients in my place of work.	23 (19.5%)	27 (22.9%)	30 (25.4%)	38 (32.2%)	2.30
I feel that patients that use the hospital I am working for always receive up to date information about their health status.	40 (33.9%)	27 (22.9%)	38 (32.2%)	13 (11.0)	2.80

Average Mean: 2.41 **Grand Average Mean: 2.26**

The level of service delivery is quite low. This is seen from the grand mean score of 2.26 on a 4 point scale. The implication of this is that the way and manner health services in tertiary institutions in Imo state is being rendered might not be anything to write home about. Some other factors might have led to this poor service delivery. This shall be examined hence. One of the indicators used to determine service delivery in this study is service ideology. This indicator attracted a low level mean score of 2.04 on a 4 point scale. Items in this particular indicator such as: "Participation in service learning activities in my place of work helped me to better understand lecture and reading materials", "My service learning experience in my place of work so far has directly influenced my record handling skills" and "I never encountered any difficulty all through my service learning experience", all attracted a mean score of 2.02, 1.91 and 2.20 respectively. This also means that health information professionals to a large extent do not participate in learning activities that much, their learning experience has not had much influence on their record handling skills and also they do always encounter difficulty all through learning experience.

Another indicator that must have contributed to low level service delivery of health information professionals in Imo state is service limits. This indicator attracted a mean score of 2.41 on a 4 point scale. Service limits has items such as "Information about patients in my place of work by myself and colleagues is well written in easy to read language, my colleagues and me do communicate effectively well with patients in my place of work and I feel that patients that use the hospital I am working for always receive up to date information about their health status". Each of this indicator attracted a mean score of 2.15, 2.30 and 2.80 respectively. This means that health information professionals in Imo state, to a large extent know that their patients receive up to date information about their health status.

Table 2. Data Processing Practices of Health Information Personnel

Items	SA	A	D	SD	M
Data Input Stage					
In my place of work, my colleagues and me follow due process in transmitting patient data from one point to another. (Data Transmission Practice)	36 (30.5%)	17 (14.4%)	40 (33.9%)	25 (21.2%)	2.55
My organization has a smooth and effective intranet for the transmission of patient data from one unit to another. (Data Transmission Practice).	10 (8.5%)	21 (17.8%)	48 (40.7%)	39 (33.1%)	2.45
My organization has effective work apparatus for data to be communicated to appropriate units for effective decisions to be taken. (Data Communication Practice)	10 (8.5%)	26 (22.0%)	54 (45.8%)	28 (23.7%)	2.65
The process of patient data communication in my organization do follow international standard of ethical considerations. (Data Communication Practice).	23 (19.5%)	27 (22.9%)	30 (25.4%)	38 (32.2%)	2.75
My organization does not stress or waste patients' time when it comes to capturing their data. (Data Capture Practice).	40 (33.9%)	27 (22.9%)	38 (32.2%)	13 (11.0%)	2.85
I have all the necessary skills to input patients' data effectively. (Data Collection Practice).	36 (30.5%)	17 (14.4%)	40 (33.9%)	25 (21.2%)	2.65
My organization has state-of-the-art facilities when it comes to collection of patient data. (Data Collection Practice).	10 (8.5%)	21 (17.8%)	48 (40.7%)	39 (33.1%)	2.50
In my place of work, I have all the necessary tools input patient data effectively and efficiently. (Data Capture Practice).	1 (.8%)	23 (19.5%)	58 (49.2%)	36 (30.5%)	2.55

Average Mean: 2.61					
Data Processing Stage					
I make sure that I follow laid down rules and regulations in processing patient data in my organization (Performing Instructions).	14 (11.9%)	23 (19.5%)	54 (45.8%)	27 (22.9%)	2.70
Regardless of my own opinion or expertise, I apply industry standard knowledge when processing patient data in my place of work (Performing Instructions).	0 (0%)	0 (0%)	57 (48.3%)	61 (51.7%)	2.60
The process of transforming patient data in my organization to information for effective decision making is always a hitch free exercise for me. (Transforming raw data into information).	23 (19.5%)	31 (26.3%)	48 (40.7%)	16 (13.6%)	2.55
Faculties available in my organization to make the process of transforming patient data into information are highly efficient. ((Transforming raw data into information).	6 (5.1%)	31 (26.3%)	62 (52.5%)	19 (16.2%)	2.45
Average Mean: 2.57					

Data input practice happens to be the most practiced form of data processing practice by health information professionals in tertiary hospitals in Imo state. This form of practice attracted a mean score of 2.61 on a scale of 4. Also items under this aspect of data processing practices, that is talking about data input practices. These items are: In my place of work, my colleagues and me follow due process in transmitting patient data from one point to another. (Data Transmission Practice), My organization has a smooth and effective intranet for the transmission of patient data from one unit to another. (Data Transmission Practice), My organization has effective work apparatus for data to be communicated to appropriate units for effective decisions to be taken. (Data Communication Practice), the process of patient data communication in my organization do follow international standard of ethical considerations. (Data Communication Practice), My organization does not stress or waste patients' time when it comes to capturing their data. (Data

Capture Practice), I have all the necessary skills to input patients' data effectively. (Data Collection Practice), My organization has state-of-the-art facilities when it comes to collection of patient data. (Data Collection Practice) and In my place of work, I have all the necessary tools input patient data effectively and efficiently (Data Capture Practice). Each of this item attracted a mean score of 2.55, 2.45, 2.85, 2.65, 2.50 and 2.55. All these mean scores were very much above the average mean score of 2.50 on a 4 point scale. This implies that truly, health information professionals in Imo state professionally do enter health records efficiently.

Another form of data processing techniques used by health information professionals in tertiary institutions in Imo state is data processing. This indicator attracted a mean score of 2.57 on a scale of 4. The implication of this mean score is that health data being processed by health information professionals in Imo state is just minimally well processed. This could also be seen from the items that buttressed this indicator. These items are: "I make sure that I follow laid down rules and regulations in processing patient data in my organization (Performing Instructions), Regardless of my own opinion or expertise, I apply industry standard knowledge when processing patient data in my place of work (Performing Instructions), the process of transforming patient data in my organization to information for effective decision making is always a hitch free exercise for me. (Transforming raw data into information) and Faculties available in my organization to make the process of transforming patient data into information are highly efficient. ((Transforming raw data into information). Each of this item attracted a mean score of 2.70, 2.60, 2.55, and 2.45 on a 4 point scale. What this implies is that faculties available in tertiary hospitals in Imo state are not effective in the process of transforming patient data into information. But on the average, data processing activities in tertiary hospitals in Imo state in quite okay.

$H_0$1: There will be no significant influence of data input on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria.

Table 3 Influence of Data Input on Service Delivery of Health Information Personnel in Tertiary Hospitals in Owerri, Imo State, Nigeria

Model Summary

Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.764[a]	.584	.581	.20185

a. Predictors: (Constant), data input stage

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.647	1	6.647	163.133	<.001[b]
	Residual	4.726	116	.041		
	Total	11.373	117			

a. Dependent Variable: service delivery

b. Predictors: (Constant), data input stage

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.745	.121		6.177	<.001
	Data input stage	.667	.052	.764	12.772	<.001

a. **Dependent Variable: service delivery**
b. **Source: Field Survey, 2023**

The result of the hypothesis revealed that data input will significantly influence service delivery of health information professionals in tertiary hospitals in Owerri, Imo State, Nigeria. This is evidenced from the probability value which was at .001, this prompted the researcher to reject the null hypothesis. Furthermore, the ***r*** value which indicated the level of relationship between the independent variable – data input and the dependent variable – service delivery was at .764. This means that the level of relationship between data input and service delivery was at 76.4%. This indicates a strong and positive relationship between data input and service delivery. The adjusted r square which indicates the level of contribution of data input to bring about service delivery was at .584. This indicates that 58.4% of data input will bring about service delivery to health information professionals while the remaining 41.6% will be based on other exogenous factors.

$H_0$2: There will be no significant influence of data processing on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria.

Table 4 Influence of Data Processing on Service Delivery of Health Information Personnel in Tertiary Hospitals in Owerri, Imo State, Nigeria

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.438[a]	.192	.185	.28149

a. Predictors: (Constant), data processing stage

ANOVA[a]

Model		**Sum of Squares**	**Df**	**Mean Square**	**F**	**Sig.**
1	Regression	2.182	1	2.182	27.536	<.001[b]
	Residual	9.191	116	.079		
	Total	11.373	117			

a. Dependent Variable: service delivery
b. Predictors: (Constant), data processing stage

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.629	.124		13.101	<.001
	Data processing stage	.304	.058	.438	5.247	<.001

a. Dependent Variable: service delivery

The probability value was at .001, this means that that the sub- independent variable significantly influenced service delivery. The ***r*** value was .438. This means that with a 43.8%% relationship between data processing and service delivery was positive but weak. The adjusted r square has a value of .192. This means that at 19.2% level of variance will data processing affect service delivery, the remaining 80.8% will come from exogenous factors.

Discussion of Finding

The level of service delivery of health information professionals in tertiary hospitals in Imo state is at 2.41 on a scale of 4. This implies that the service delivery performance level of health information professionals in Imo state is quite low. The implication of this is that According Adane, Gizachew, & Kendie, (2019) poor medical record management is the reason for deficient health delivery and that using high-quality electronic health record (EHR) applications in health care is important to minimize medical errors.

The second research question of this study says "What are the different data processing practices adopted by health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria?. The answer to this research question reveals that data input is the most practiced form of data processing by health information professionals in Imo state. This particular indicator attracted a mean score of 2.62 on a scale of 4. This means that to a large extent health information professionals in Imo state do practice data input of health records effectively. A situation whereby data input of health records is effectively done, it is expected that patients will effectively get prompt medical care that they need. This is possible in the sense that, when Doctors and other healthcare practitioners have access to quality medical records, they will be able to give quality medical care to patients as well (Adane, Gizachew, & Kendie, 2019).

The null hypothesis which says "There will be no significant influence of data input on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria". The null hypothesis was rejected because indeed, data input will definitely bring about service delivery. Studies have actually shown that this is true. In the sense that when health records are effectively inputted, to a large extent the health record information professional will definitely be effective in discharging her duties (Abd-Alrazaq, Bewick, Farragher, & Gardner, 2019; Waithera, Muhia, & Songole, 2017). The second null hypothesis says that "There will be no significant influence of data processing on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria was rejected (Adane, *et al*, 2019; Bardhan, & Thouin, 2013; Iyamu & Nunu, 2021). This means that data processing has a significant influence on quality healthcare delivery as it serves as a reliable ground upon which quality health decisions are made.

Conclusion

Specifically, this study found that Service delivery of health information professionals in tertiary hospitals in Owerri, Imo state is quiet low. More so, data input practice of health information professionals in tertiary hospitals in Owerri, Imo state is pretty much effective and it is being done in a professional way.

This study has revealed the essence of service delivery among health information professionals in Owerri, Imo state. Three factors has been largely seen to affect service delivery of health information professionals in the state, they are: data input, data processing and data output. The study has also been able to reveal that a combination of data input, data processing and data output will bring about quality in healthcare service delivery. Furthermore, data storage as an indicator of service delivery, when it is nothing to write home about among health information professionals, it could actually bring about low level service delivery.

Recommendation

Going by the findings of this study, the following recommendations are hereby postulated:

1. State-of-the-art facilities have got to be provided to enable effective and efficient method of health data storage among health information professionals in Owerri, Imo state.
2. Health information professionals in Imo state have got to be orientated that when health data is wrongly imputed, it must be corrected immediately.
3. The place of training and retraining is inevitable as it would equip health information professionals with the necessary competences needed in the wake of the obstructive nature of technological innovations.

References

Abd-Alrazaq, A. A., Bewick, B. M., Farragher, T., & Gardner, P. (2019). Factors that affect the use of electronic personal health records among patients: a systematic review. *International Journal of Medical Informatics*, *126*, 164-175.

Adane, K., Gizachew, M., & Kendie, S. (2019). The role of medical data in efficient patient care delivery: a review. *Risk management and healthcare policy*, 67-73.

Al Kiyumi, R. H. M., Walker, S., Tariq, A., & Fitzgerald, G. (2016). Health information management professionals [Present circumstances and future expectations]. In *Proceedings of the 18th IFHIMA International Congress* (pp. 518-529). International Federation of Health Information Management Association.

Amollo, B. O. (2021). *Evaluation of School Management Information Systems (Smis) in Secondary Schools in Siaya County* (Doctoral dissertation, JOOUST).

Austin, M. J., &Carnochan, S. (2020). *Practice research in the human services: A university-agency partnership model*. Oxford University Press, USA.

Bardhan, I. R., & Thouin, M. F. (2013). Health information technology and its impact on the quality and cost of healthcare delivery. *Decision Support Systems*, *55*(2), 438-449.

Boussaid, O., Tanasescu, A., Bentayeb, F., & Darmont, J. (2007). Integration and dimensional modeling approaches for complex data warehousing. *Journal of Global Optimization*, *37*, 571-591.

Corsi, A., de Souza, F. F., Pagani, R. N., & Kovaleski, J. L. (2021). Big data analytics as a tool for fighting pandemics: a systematic review of literature. *Journal of Ambient Intelligence and Humanized Computing*, *12*(10), 9163-9180.

Emetere, M. E., Akinlabi, E. T., Emetere, M. E., & Akinlabi, E. T. (2020). Data Treatment. *Introduction to Environmental Data Analysis and Modeling*, 157-214.

Hamad, F., Al-Fadel, M., & Fakhouri, H. (2022). The role of academic libraries and information specialists during times of health crises in Jordan: the COVID-19 pandemic case. *Digital Library Perspectives*, *38*(4), 476-492.

Heip, C., Herman, P. M., & Soetaert, K. (1981). 14. Data Processing, Evaluation, and Analysis.

Iyamu, T., & Nunu, K. (2021). Healthcare data management conceptual framework for service delivery. *Education and Information Technologies*, *26*, 3513-3527.

Kumar, G. (2023). Critical Success Factors of Adopting an Enterprise System for Pharmaceutical Drug Traceability. *Universal Journal of Pharmacy and Pharmacology*, 3-10.

Kusakunniran, W., Karnjanapreechakorn, S., Siriapisith, T., Borwarnginn, P., Sutassananon, K., Tongdee, T., &Saiviroonporn, P. (2021). COVID-19 detection and heatmap generation in chest x-ray images. *Journal of Medical Imaging*, *8*(S1), 014001-014001.

Ma, J., Stahl, L., & Price, C. (2020). Developing specialized graduate curricula for health information professionals: Integrated findings of a scoping review and an employer survey. *Journal of Education for Library and Information Science*, *61*(1), 64-86.

Medeiros, M. M. D., Hoppen, N., &Maçada, A. C. G. (2020). Data science for business: Benefits, challenges and opportunities. *The Bottom Line*, *33*(2), 149-163.

Mogli, G. D. (2009). Medical records role in healthcare delivery in 21st century. *Acta Informatica Medica*, *17*(4), 209-212.

Nath, R. P. D., Romero, O., Pedersen, T. B., & Hose, K. (2020). High-Level ETL for Semantic Data Warehouses---Full Version. *arXiv preprint arXiv:2006.07180*.

Provost, F., & Fawcett, T. (2013). Data science and its relationship to big data and data-driven decision making. *Big data*, *1*(1), 51-59.

Safiri, S., Sepanlou, S. G., Ikuta, K. S., Bisignano, C., Salimzadeh, H., Delavari, A., ... & Mirzaei, H. (2019). The global, regional, and national burden of colorectal cancer and its attributable risk factors in 195 countries and territories, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. *The lancet Gastroenterology & hepatology*, *4*(12), 913-933.

Spatar, D., Kok, O., Basoglu, N., & Daim, T. (2019). Adoption factors of electronic health record systems. *Technology in Society*, *58*, 101144.

Urooj, A., Nafis, M. T., & Ahmad, M. (2021). An Analytical and Comparative Study of Hospital Re-admissions in Digital Health Care. In *Computer Networks, Big Data and IoT: Proceedings of ICCBI 2020* (pp. 717-733). Springer Singapore.

Waithera, L., Muhia, J., &Songole, R. (2017). Impact of electronic medical records on healthcare delivery in Kisii Teaching and Referral Hospital. *Med Clin Rev*, *3*(4), 21.

Woolf, S. H., Chan, E. C., Harris, R., Sheridan, S. L., Braddock III, C. H., Kaplan, R. M., ... & Tunis, S. (2005). Promoting informed choice: transforming health care to dispense knowledge for decision making. *Annals of Internal Medicine*, *143*(4), 293-300.

World Health Organization. (2020). Operational framework for primary health care: transforming vision into action.