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

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## Certification

This is to certify that this thesis was carried out by **Christian Chimezurum NWANKWO** with Matriculation Number **LCU/PG/002527** a student in the Department of Information Management under my supervision in the Faculty of Communication and Information Science, Lead City University, Ibadan, Nigeria

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**Dedication**

This Thesis work is dedicated to the Almighty God for his Grace, Favour and protection.

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## Abstract

Without the presence of health information professionals in a health institution, a whole lot of damage will be done to patient records. How effective health information professionals are has a whole 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. In the absence of deficient data processing practices, service delivery of health information professionals will always be questioned. 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 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. The study revealed that three out of the four components (data input, data processing and data storage) used to measure data processing output did significantly influenced service delivery (($R^2$ = 0.001; P >.05). While data output did not significantly influence service delivery (R2 = .002; p < .622). From a joint perspective, only data storage was found not to significantly influence service delivery (Adjusted $R^2$ = .685, F(61.541 = 3.578; p > 0.05). The study recommended that Health Information Professionals have got to be trained very well for them to know how to use state-of-the-art facilities to store health data effectively.



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


**Word Count: 292**

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# CHAPTER ONE

## Introduction

### 1.1 Background to the Study

Health care remains one of the global indices of measuring human existence; this is because quality health care contributes to the maximum enjoyment of achievable quality wellness, which is one of the fundamental rights of every human being irrespective of race, ethnicity, political ideology, economic or social status. Health can be described as a condition of being free from disease or injury. It refers to the mental or physical condition of a person, physical wellbeing, mental and social wellness where disease and infirmity are absent. Service delivery is a business framework that supplies services from a provider to a client. It also includes the constant interaction between the two parties during the duration of the time in which the provider supplies the service and the customer purchases it. Service delivery of health information personnel is the act by which health information personnel keep, process, maintain, and deliver patients' data to enhance patients' health status.

Health information professionals who want to make a difference for their patients should work to improve the quality of care provided by tertiary hospitals. Reduced costs, more accessible services, efficient operations, and higher quality service are all desirable results that service delivery systems should be able to provide. What we mean by "service delivery" is providing clients or patients with the actual data processing services they have requested[1]. It is therefore concerned with the where, when, and how service is delivered to the patients and whether this is fair or unfair in nature.

Public health decision-making is seriously reliant on a timely availability of sound data, and globally significant human and financial resources have been invested to improve health information systems[2]. While information technology have helped improve data monitoring and

evaluation, demand for data and information use in decision-making has typically been low. As a result, many healthcare systems are unable to adequately respond to top health priorities because they are not properly linking evidence to decisions. It is generally understood that the data created by healthcare systems is utilized for a variety of purposes, including but not limited to planning, managing health commodities, spotting outbreaks, and monitoring the overall performance of the healthcare system to ensure that high standards of treatment are consistently met[3].

Any time health information professionals interact with a patient's medical records in order to update or correct them for the benefit of healthcare providers, they are providing a service[4]. 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. 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[5].

Medical care is an example of an intangible good because it cannot be physically held or examined. They are singular experiences that cannot be duplicated or transferred to another person. Health information professionals use data from patients to improve service delivery and data accessibility. The quality of health information services provided by Owerri's tertiary hospitals will vary greatly due to the fact that services exist as events and thus are more subject to variation than other items an organization can produce. It will take a lot of work on the part of the hospitals to raise the bar on service quality and uniformity. Many ideas of providing social services highlight the significance of the hospital's own internal ideology. A bigger mission that

would increase better service delivery from health information personnel in the hospitals is needed to encourage the health information personnel at each tertiary hospital in Owerri and give them with wide guidelines. Constraints: A hospital's service is fundamentally constrained by the available number of health information employees. There is a limit to how much a single member of the information staff can do in a given period of time. Since the difficulty of a service directly correlates to its price, it is common practice to hire more people to work on it in order to improve its quality or output. As a result of a shortage of staff and an absence of necessary IT resources, health information services provided by tertiary institutions in Owerri are subpar.

In spite of the robust structure of healthcare service providers in Nigeria and Imo State, the healthcare services facilities in the state are deplorable and seriously militated by inadequate funding. This has had a negative impact on technologically driven data processing and services delivery, such as the provision of a suitable power supply, poor ICT facilities, and right access roads to the available health care facilities[6]. The inability of the state to meet the requirements of its residents with regard to health care has resulted in the proliferation of several private health care institutions that are priced beyond of reach for the typical person. Creating a technology-driven health data processing system in Owerri's tertiary hospitals is the solution to this problem. This will, without a doubt, ensure that the patients receive quality services, and it will also ensure that the necessary health information technical equipment is available.

Within the framework of a comprehensive health system, data processing procedures are functional entities that are intended to improve both the health of individuals and the health of the population as a whole. When it comes to the process of making decisions, both medical and paramedical workers can rely on the specialized information assistance that is provided by the management system. With the resources that are available, the data processing structure should make it possible to generate all of the required information that can be incorporated into

decision-making at each level of the healthcare system. When data are collected and converted into information that can be used, this process is known as data processing. It is critical that the processing of patient data be carried out accurately so as not to have a negative impact on the patients' health. The processing of data begins with the data in its raw form and changes it into a format that is easier to read. This gives the data the shape and context that is required for it to be interpreted by computers and utilized by health information specialists in tertiary hospitals in Owerri, which is located in the state of Imo.

When someone receives information, they get insight into the world. Data is the term used to describe information that has been entered into a computer[7]. Raw input is known as data, and the result of processing this data is known as information. Nowadays, data is stored in a wide variety of devices and presented in a wide variety of formats. The health care industry has a critical need for convenient, timely, and well-organized access to relevant data. To generate, transmit, and preserve healthcare information, health data processing procedures incorporate a wide variety of networking technologies, clinical databases, electronic /health records, and other specialized biomedical, administrative, and financial technology. A patient's whole medical history can be found in an electronic health record that includes information from hospitals, clinics, emergency rooms, small offices, and multispecialty groups. This data is then electronically transmitted across a nationwide network[8].

Standardizations for prevention and treatment, in turn processed to yield information for decision-making and decision-support, are generated from data flows from electronic health records and regional registries maintained by hospitals. An individual's health data is processed when it is created and collected electronically across multiple health care organizations, then managed and consulted by licensed clinicians and staff involved in the individual's health and care[9]. Standards for both data transmission and data definition are crucial to the effective

operation of the application system. The data input, processing, output, and storage phases make up these processes[10].

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[11]. Data 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. The first thing to do is figure out what kind of data is required and how it will be collected.

The problem with Owerri, Imo State's tertiary hospitals is poor data entry, which occurs when data is accessible in an illogical sequence or when the instrument used to access the data is inadequate. Decision-makers at all levels would benefit from investing in the development of effective health information systems because it would allow them to: detect and control emerging and endemic health problems; monitor progress towards health goals; promote equity; equip people and communities with health information that is both timely and easy to understand; drive improvements in service quality; strengthen the evidence base for effective health policies; allow for the evaluation of the impact of health interventions.

The majority of health information workers' days are spent collecting massive troves of client and patient data that are rarely examined and used immediately. Medical personnel only compile data and report it on in aggregate to higher authorities. At the level at which data is acquired, this information is rarely used to direct local action. Despite the fact that health information systems are primarily intended to make administrators' lives easier, very little data ever makes its way to those in charge. One possible explanation for this is because information consumers were not consulted throughout the development of these tools.

Data processing and reporting is one area that can help patients get the care they need. Lack of understanding the requirement for accuracy and completeness in the processing of health records may be hampered by the limited education of processing workers. The reliability of their data will suffer if they are not given adequate training. Furthermore, health information staff fail to adequately plan for the implementation of data quality control initiatives. Finally, in the case of tertiary hospitals in Owerri, Imo State, data inconsistencies arise when errors occur at the time of collection and may lead to inaccurate information upon reporting of data for action.

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[12].

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[13].

The data output stage describes the process of actually using the data. These details are collected into data sets that are much larger and more intricate than those required by standard data processing software. As a result, analysis, collection, data curation, search, sharing, storage, transfer, visualization, querying, updating, and information privacy remain persistent issues due to the nature of the institutions and the massive accumulation of patient data. 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[13]. 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[13].

Hospital and health system leaders used varied approaches to demonstrate that implementing electronic health records was a high priority. All of the hospitals committed significant financial resources toward equipment, software, IT staff, and training[14]. In addition to training hospital staff, integrated health systems trained physicians in their owned and affiliated practices that were adopting the medical office version of the electronic health record. And most also offered training to community physicians who had different office medical record systems but admitting privileges; this enabled them to add to the medical record when treating patients at the hospital and to access information from the electronic health record of their patients. Hence, with the above discussion, this study will investigate the influence of data processing practices on service delivery of health information personnel in Owerri, Imo State, Nigeria.

## 1.2 Statement of the Problem

Service delivery ensures that health information personnel in Owerri, Imo State meet the goals and objectives of tertiary hospitals in Owerri, Imo State. It ensures proper health data input, data processing, data storage and data output of patients that patronize tertiary hospitals in Owerri. When service delivery of the health information personnel are ensured, data will be processed, stored, retrieved and disseminate appropriately without missing patients' records. Preliminary investigation, close observation and literature review indicate that data are not produced on time when needed by the administrative units and that it was virtually impossible to retrieve the required information from old files due to insufficient technology for data processing[15]. It's possible it's not an exaggeration to claim that all tertiary hospitals face issues with data processing at some point or another. However, it is becoming increasingly apparent that this problem is particularly severe in healthcare facilities, where data that is accurate, reliable, and trustworthy and meets evidentiary criteria is being generated but is not being handled effectively. Governments, healthcare providers, and the general public all have a vested interest in finding a solution to this problem. Data processing practices appear to still be conventionally paper-based and manual in operation, despite past frantic efforts to improve the situation in many tertiary hospitals through the introduction of computers and internet services and the development of database management system. There appears to be a lack of ready access to data concerning the operations of the various tertiary hospitals.

Service delivery of health information personnel on data processing practices are lagging; and this could have adverse effects on tertiary hospitals' decision making and health delivery, performance and the reputation of the hospitals will also decline. This prompted this study to fill in the gap to provide information on data processing practices and service delivery of health information personnel in Tertiary Hospitals in Owerri, Imo State, Nigeria.

### 1.3 Aims and Objectives of the Study

The aim of this study is to investigate the influence of data processing practices on service delivery of health information personnel in Tertiary Hospitals in Owerri, Imo State, Nigeria. The objectives of the study are to:

i. assess the level of Service Delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria;

ii. examine the prevalent data processing practice adopted by health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria;

iii. ascertain the influence of data input on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria;

iv. determine the influence of data processing on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria;

v. ascertain the influence of data storage on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria;

vi. determine the influence of data output on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria;

vii. determine the combined influence of the measures of data processing practices (data input, data processing, data storage and data output) on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria.

### 1.4 Research Questions

In order to achieve the aim of the study the following research questions were considered.

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

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

### 1.5 Hypotheses

The following are the research hypotheses that will be tested in this study at 0.05 level of significance.

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

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

**$H_0$3**: There is no significant influence of data storage on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria.

**$H_0$4**: There is no significant influence of data output on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria.

**$H_0$5**: There is no significant combined influence of the measures of data processing practices (data input, data processing, data storage and data output) on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria.

## 1.6 Significance of the Study

This study will be of great use to Health Information Personnel, management of tertiary hospitals and for future researchers undertaking studies in Health Data Processing Practices.

It will create awareness of how to manage data effectively with minimal stress for health information practices with the provision of necessary ICT equipment and giving health information personnel required training in managing health data appropriately. This study if well adopted will ensure that tools for data processing practices enhance the systems by strengthening their health sector capacity in terms of the training of staff at different levels. It will make sure it provides a professional approach for training/learning policy, design, implementation and evaluation. The management of these tertiary hospitals will also benefit as the study will illuminate the stale areas of data processing among tertiary hospitals and also create awareness on how to manage data more effectively with less stress. Patients will not be left out as they will begin to enjoy the blessings of getting required data in their accurate form and within a small space of time.

This study will give government and management of tertiary Hospitals in Owerri and Imo State the better policies to enhance data processing practices, they will also provide necessary equipment to enhance data management in the hospitals and boost their duties with the right management support.

It is hoped that the study will be an invaluable contribution to the only small amount of work that has been done on the lingering issue of tertiary hospitals data processing and that it will provoke more researches which will largely draw more attention to this important subject. The findings of this study will benefit future researchers by serving as reference for students and future researchers on better approaches to data processing practices, and service delivery of health information personnel in Owerri, Imo State, Nigeria.

## 1.7 Scope of the Study

The study concentrated on the influence of data processing practices on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria. The measures of service delivery are service intangibility, service ideology, service variability and service limits. The measures for data processing practices are data input stage; data processing stage, data storage stage and data output stage. The geographical scope of the study covered health information personnel of tertiary hospitals in Owerri, Imo State, Nigeria which include, Federal Medical Centre, Owerri and, Imo State Specialist Hospital Umuguma, Owerri. The respondents are all health information personnel in tertiary hospitals in Owerri.

## 1.8 Limitation of the Study

The major limitation of the study is that the respondents were not willing to provide necessary data for the study. The researcher had to make some clarification and assure the respondents of their anonymity and the intention to use the data collected only for the purpose of research.

## 1.9 Operational Definition of Terms

**Service Delivery:** It is the measure of performance level delivered by health information personnel in Owerri, Imo State, Nigeria.

**Service Intangibility**: This refer to the fact that health information services are not physical, they cannot be touched nor handle among health information personnel in Owerri tertiary hospitals.

**Service Ideology:** This is the believe/norms that guide health information personnel in executing their duties in tertiary hospitals in Owerri, Imo State.

**Service Variability:** It is the changes in the quality of the same service provided by different health information personnel in tertiary hospitals in Owerri, Imo State.

**Service Limits:** This is the maximum elevation to which health information personnel in tertiary hospitals in Owerri, Imo State can exercise their duty.

**Data Processing Practices:** It is the conversion of raw health data of patients in tertiary hospitals in Owerri, Imo State to readable health information.

**Data Input Stage:** This is the process of gathering and measuring patients' information which enables medical consultants to answer relevant questions regarding the health of a targeted patients in tertiary hospitals in Owerri, Imo State, Nigeria.

**Data Processing Stage:** It is the process of inspecting, cleansing, transforming and modeling patients' health information with the goal of discovering useful information by medical consultants in tertiary hospitals in Owerri, Imo State, Nigeria.

**Data Storage:** It is the central repository of information that can be processed to make more informed decisions on the health records of a particular patient in tertiary hospitals in Owerri, Imo State, Nigeria.

**Data Output Stage:** It is the process of analyzing large-scale health data of a patient to quickly surface rich insight or take autonomous action by medical consultant in tertiary hospitals in Owerri, Imo State, Nigeria.

**Health Information Personnel:** They health professionals that are essential in quality programs and provide guidance on documentation, communication, electronic health implementation and electronic health records in tertiary hospitals in Owerri, Imo State, Nigeria.

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# CHAPTER TWO

## Literature Review

This chapter tends to examine the various research works that has been carried out by eminent scholars on the Data Processing Practices as Correlates of Service Delivery by the Health Information Personnel in Tertiary Hospitals in Owerri, Imo State, Nigeria. The following sub-headings are as follows:



### 2.1 Conceptual Review

#### 2.1.1 Overview of Service Delivery

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[1].

Service delivery is the 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[2]. Data processing service delivery is the aggregate electronic record of health related information on an individual that is created and gathered cumulatively across more than one health care organization and is managed and consulted by licensed clinicians and staff involved in the individual's health and care. Information is the knowledge which gives meaning to its receiver. When a person stores some information into the computer, it can be referred as data.

Raw input is known as data, and the result of processing this data is known as information. Nowadays, data is stored in a wide variety of devices and presented in a wide variety of formats. It's crucial to have quick, easy access to relevant data at just the appropriate moment. Recent years have seen considerable increases in the resources mobilized for health, for example through the Global Fund for HIV/AIDS, TB, and Malaria, which has contributed to a rising need for high-quality health information[3]. Performance-based disbursement systems necessitate frequent monitoring of short-term programme outputs (such as improvements in service

provision and the number of people using such services) in the context of such global initiatives, and reporting requirements for countries are being increased as a result. Additionally, better reporting of health outcomes, such as increases in life expectancy and quality, is essential for keeping tabs on global initiatives like the Millennium Development Goals (MDGs).

However, data needs arising from worldwide and disease-specific initiatives tend to center on specific indicators and do not automatically translate into constructing systems that suit the objectives of both countries and the international community. There has not been enough money put into developing efficient health information systems capable of producing data on the full spectrum of health-related concerns, therefore the current spike in demand for health information cannot be satisfactorily supplied. Improving the efficiency of a company's healthcare systems is greatly aided by meticulous data management. Health care workers may see where their systems are lacking, make modifications, and monitor results by collecting, analyzing, interpreting, and acting on data for specified performance measures. Information on how to collect, analyze, evaluate, and act on data for a given performance measurement is provided in this module, along with guidance on how to better comprehend the connection between quality improvement and data management[4].

A health information system "is a collection of components and procedures organized with the goal of generating information which will improve health care management decisions at all levels of the health system," as defined by the Institute of Medicine. Personnel in the field of health information gathers data needed for health decision making from the health industry and allied industries, evaluates health data for accuracy, timeliness, and relevance, and then transforms the data into usable information. Obtaining, reporting, and using information to support policy making, program intervention, and involving professionals on research are all crucial to the smooth operation of health systems around the world[5]. Those working in health

information management are responsible for maintaining a database of data about patients, medical practitioners, and other healthcare providers, as well as the systems and infrastructures through which they interact.

The term "health information system" (HIS) refers to any collection of health-related data that follows a consistent framework. Health services research is the process of gathering information that can be utilized to improve health care delivery or to promote health development on a national scale. The availability of accurate and timely data is crucial to the success of health planning and policy choices, as well as the standard of treatment provided to patients[6].

Tertiary hospitals health services include the prevention and management of mental illness, which is often caused by anxiety[7]. No of the price tag, good health care in any community should prevent an uptick in the number of people experiencing health problems. Information about the work of medical professionals, such as primary care physicians, dentists, nurses, psychologists, and others, is also an important part of a comprehensive public health system. Both in rich and developing countries, academics have studied various aspects of public health service delivery. Some of these academics looked at how often people really use public healthcare, while others delved into how satisfied they were with the treatments they received. Several of these researchers have focused on gauging the state of children's health, while others have focused on the aging population.

Prevention of preeclampsia among pregnant women will reduce maternal mortality in underdeveloped nations, just as it does in developed countries, according to an analysis of preeclampsia perspectives in global health and its implications for fortifying the health system. It has been suggested in the literature that a government's top goal should be to increase the

availability of and access to maternal health services in order to improve the functional health and well-being of its citizens[8].

According to the findings, health services continue to place a priority on preventing pregnancy-related disorders. Many Nigerian public health service institutions have observed low rates of mothers using their maternity wards. Similarly, authors have investigated the correlation between age-specific mortality and various health care indices to gauge the efficacy of public health initiatives. Different scientists, each with their own medical background and perspective, have tried to assess the quality of tertiary health care in their own nations, as evidenced by the literature[9]. Academics are concerned with how well and how far their countries have come in providing primary health care to their overburdened populations.

The facts and numbers show that health service delivery has underachieved in many countries around the world, including Nigeria. This is due to a lack of investment in fundamental medical sectors like the expansion of basic health services at primary care clinics and the maintenance of an effective information technology infrastructure. These were the case because many providers of health care had failed to treat the ill and injured at reasonable prices. There are problems with the inequitable allocation of medical resources across the country, which is a reflection of the needs of the less affluent, as has been noted in the literature[9]. On top of that, several public health systems have been criticized for failing to strategically formulate strategy across all public health care facilities. Many nations with inadequate infrastructure also have poor public health care drivers. Many people in countries like Nigeria and Pakistan have low incomes and limited access to healthcare because of factors such as ingrained cultural norms, the suppression of women's agency, inadequate financial resources, and widespread sickness.

Individual health outcomes may be influenced by the level of health literacy of the population, which is why health information professionals emphasize it. That instance, people with less education may be unaware of the basic health care options available to them. The authors have shown that people with higher literacy levels are more likely to value their health and make conscious efforts to enhance it. Researchers have found a correlation between health literacy and health outcomes in a related investigation. It's also been established in the literature that money plays a crucial role in providing high-quality public health care. The decentralization of Nigeria's healthcare system has been plagued by a lack of accountability and transparency, which has had a devastating effect on the quality of tertiary care provided to the country's citizens. Recent years have seen discussions on the effectiveness with which medically-focused public officials have used the funds allotted to their field to better the health care system in their respective regions. To move forward from the current global health service status, that significant improvement is required, which is necessary to achieve the delivery of health services Millennium Development Goals. The health and well-being of the population as a whole has improved, and the rate of maternal mortality has decreased[10].

Public health institutions must embrace the power of the modern framework for handling health information in order to improve public health services, which is currently the primary factor in the efficient delivery of health care services on a global scale. According to the International Organization for Standardization (ISO), health data is any information on a person's or company's physical or mental health that is created, received, or held in connection with a commercial transaction or the enforcement of legal obligations. Therefore, HISs continue to be a viable option for managing patients' medical data, which could improve the quality of care they receive[11]. The health information system is frequently linked with monitoring and assessment. In addition to being essential for monitoring and assessment, the health information system also

serves broader goals, provides an alert and early warning function, aids in patient and health facility management, facilitates the preparation, funding, and stimulation of research, enables the analysis of health situations and trends, promotes regional coverage, and communicates health issues to a wide range of consumers. Without making it easy for politicians, planners, administrators, healthcare providers, communities, and individuals to access data, it serves no useful purpose. Scholars have suggested that the clinical workforce increasingly requires rapid dissemination of patient health information.[12].

Similarly, a healthcare information system is a database and research tool for the healthcare industry. There is no universally accepted definition of a health information system or its administration. Commonly, it refers to the typical paper or digital health record format. Public health facilities all across the world create vast amounts of patient health data every day. Unfortunately, patients' vital medical and health records have been deteriorating due to inefficient handling of this data. Despite this, research has shown that the depth of knowledge about health management methods varies not only between healthcare facilities but also between nations[13]. The current system of healthcare provision typically dictates data processing procedures. It was determined, for instance, that public hospitals of all sizes and locations in South Africa, Nigeria, and the rest of Africa had struggled for decades with poor health service delivery.

Therefore, it may be concluded that a country with low-quality public health care delivery will likewise have low-quality processes for dealing with health knowledge. It was determined that subpar healthcare services may be provided if medical records are not managed properly, and that healthcare institutions will collect inaccurate, outdated, incomplete, and/or fake data if medical records are not properly preserved[14]. The study's author contended that when records aren't properly stored, they're more likely to get misplaced, tampered with, misfiled, or even

destroyed, making it difficult to track down and wasteful of valuable time. Such records are of little use to healthcare professionals in areas such as issue solving, reporting, and assessing service quality in order to improve their services on an ongoing basis. Legal mechanisms for record management procedures are still not devised, let alone executed, and there are no records of the operation or implementation of the corporate services department in the Ministry of Health. In addition, the records manager and other records administrators would have their training needs specified by this administration[15].

It was reemphasized that effective data processing is crucial for governments to "achieve and meet their goals," including upholding the rule of law, being transparent, keeping tabs on state resources, protecting citizens' rights, and fostering better international relations. Based on the idea that "effective information and data management lays the groundwork for accountability, protection of human rights, and increased citizens' sensitivity to their rights," the author develops an argument[16]. A researcher looked at medical records and the Healthcare Facilities' management history. The author discovered that many hospitals' inability to make sound decisions was due to a flawed health information management system. The research found that an electronic health records management system should be implemented since it better ensures the safety of patients' medical records and makes it easier to access them when needed. A researcher in Nigeria looked at two hospitals in Lagos State and documented the management issues they were having. Their research showed that low-level health information management was the result of insufficient funding, a failure to incorporate electronic health information programs, and a lack of implementation of records preservation and conservation policies[15].

Researchers in a similar vein evaluated data management's impact on the quality of secondary healthcare delivered by government-run facilities in Osun State, Nigeria[17]. Misfiling, misplacing, overcrowding, and limited storage space were found to be the result of a lack of uniform

management policy, a lack of legal authority for the disposition of records and documents, a lack of funds for the procurement of standard filing shelves and cabinets, and a lack of consideration by hospital administrators, according to their study. A researcher looked into the opportunities and obstacles presented by the widespread adoption of electronic health records in Nigeria's secondary healthcare facilities. According to his findings, health records are important to medical progress. Another academic has echoed the importance of high-quality health care data in facilitating effective healthcare system planning, development, and upkeep. The methods of health information handling must inevitably revolve around medical records management, which includes but is not limited to a written record of the patient's diagnosis and care, including the patient's history of the condition and complaints; the physician's observations; and the results of laboratory tests, protocols, medications, and treatment protocols.

Both a formal commercial healthcare sector that is resource-intensive and highly specialized, and a resource-constrained public healthcare sector provide healthcare. Due to the country's high poverty and unemployment rates, residents of South Africa often turn to the publicly funded services provided by the government when they lack the resources to pay for private medical care[18]. The private healthcare sector is run by for-profit healthcare corporations and caters to those who can afford to pay for its premium services. Overcrowding in hospitals and clinics due to a lack of beds is just one symptom of the public health system's larger problem: a dearth of trained medical professionals. Poor service delivery, long lines and wait times at health institutions, low literacy, scarce resources, and an absence of health information systems disproportionately affect rural people.

Healthcare professionals in both urban and rural areas, including tertiary hospitals, continue to mostly use paper medical records. There are many problems associated with paper-based health records, such as inadequate data, lost patient records, and illegible handwriting. Health records

have been reported missing or stolen in a number of instances in South Africa, including the following: A nurse at St. Elizabeth hospital in Lusikisikis, Eastern Cape Province, South Africa, was reported by the Eastern Cape Department of Health to have been caught trying to steal a patient's medical data. A lawsuit against the health department was allegedly planned by the nurse in consultation with legal counsel. According to one scholar's research, missing patient data caused a number of issues for healthcare providers, including delays in providing high-quality, dependable services and a lack of insight into earlier diagnoses made on patients at the point of care[18].

According to the study's author, doctors refused to treat a patient with diarrhea until the staff spent more than eight hours hunting for his medical records[19]. "When he arrived at the file room, an employee instructed him to rummage through the stacks of folders on the floor and the shelves to find his own medical record." From Monday through Friday, the hospital distributes between 750 and 1000 cards. The filing department occasionally has trouble locating medical records due to factors such as misfiling and lost documents. Cases like this make it clear that patients face serious risks to their health and even death when paper copies of their medical data go missing. The health system as a whole may suffer as a result of this. Many institutions and systems struggle with the fact that duplicate patient data is seen as unreliable and of low quality. The inability to easily transfer data between several users is yet another drawback of paper-based medical records, which are typically only accessed in the actual area where the document is kept[20].

Accessibility in the physical sense can refer to the availability of information through public, social, or private channels. A cancer care facility, a public library with Internet access, or a widely circulated newspaper or magazine are all good examples of publicly available sources of information. Although freely accessible, some sources may require additional investment before

they may be used. Information obtained via a friend, partner, family member, neighbor, or coworker who has access to the Internet is considered a socially available source. Last but not least, people can access information in private settings, such as their own homes, using means such as television, the internet, and telephone advice lines[21].

Information is considered personally retrievable if and only if a person has the resources (financial, time, skill, knowledge, mobility, understanding, emotional strength) to access and use it. How complicated or important various data sources are will determine the answer. Having a social network to rely on may improve one's physical accessibility and ease of retrieval. A person's accessibility to resources can be improved through the provision of instrumental and informational support, such as the loan of a computer or transportation to a public library. Helping someone grasp the knowledge they have or providing the emotional support they need to ask questions or seek more information might increase their own retrievability[22].

A patient's or family member's information utilization (the number and variety of sources they consult) has been found to be largely influenced by both their perceived need for knowledge (a patient who does not desire information will not seek it) and the ease with which they can obtain that information. A person's level of contentment with a given piece of information depends not only on how well it satisfies an immediate need, but also on their prior knowledge and expectations, as well as their unique character traits. Patients with higher depression scores were also more likely to be unsatisfied with the health information they had received, and we discovered that breast cancer patients expected more information than prostate cancer patients.[23].

There are many patient groups where information and education is part of the treatment. For example, we developed a multimedia system for cognitive behavioral therapy in the management of anxiety[24]. Thirty-one participants scheduled appointments with a research assistant and used a

computer at a health center as part of a pilot project. The research assistant had to keep the computer on a trolley and wheel it to a vacant conference room every time an appointment was scheduled. After six months, most patients reported significant reductions in anxiety. However, proof of its usefulness in everyday primary care settings was required. We investigated potential locations for the computers in health centers and public libraries in Glasgow to solve the issue of where to put the computers. We were only able to locate one computer in a hospital, but many in local libraries. Patients were referred to the experiment by primary care physicians and recruited from ten public libraries and one health center. The majority of the study's 178 participants (74%) met at a public library, out of a total of 239 patients referred by their doctors. This proved that those in need of 'therapy' based on information might be referred to public libraries. Almost every public library in the United Kingdom now provides Internet connection, thus it could be beneficial to conduct a test of their use in major cities[24].

Some scholars examined anxiety levels over the course of the study's three months since some previous authors had speculated that providing cancer patients with access to their own medical information would increase anxiety[25]. Despite our expectations, we discovered that patients whose anxiety was addressed with general information improved less than those whose anxiety was addressed with information based on the medical record. We reasoned that this might be because patients who received individualized information would talk about it with their loved ones at home. We just finished collecting data for a randomized trial designed to test that theory, with a primary emphasis on the paper format. A paper leaflet's main benefit is that it can be shared as a reference with close friends and family. Four hundred patients and their "significant others" have been enrolled in the study. The data collection phase is complete, however the analysis is still under progress. The social contacts fostered and the anxiety experienced are the primary foci of our investigation into the effects of various leaflet distribution strategies. We'll

start by simulating how patients are more or less likely to use booklets at home depending on whether or not they were given a say in what was included, (b) had access to their own medical records, and (c) received guidance on how to cope with worry. Second, we'll model patients' levels of anxiety three months after treatment as a function of these three characteristics and their leaflet use at home. We hypothesize that people are more inclined to confide in their "significant other" about private matters when that information is tailored to their own needs[26].

For effective pharmacological therapy, it is crucial that up-to-date health and pharmaceutical information be readily available in all healthcare settings. Competence in using health and pharmaceutical data sources and databases, which are increasingly available in electronic formats, is necessary for the appropriate future use of this information in clinical practice. These skills can be learned in post-secondary programs, as well as through in-house training. Undergraduate students can benefit from internships and other work-based learning opportunities in real workplace settings by gaining hands-on experience in areas such accessing Health and pharmaceutical data sources. Patients in ambulatory care settings benefit greatly from the involvement of community pharmacists in medication management through services such as medication counseling and the detection, resolution, and prevention of medication-related issues. Numerous clinically relevant, current, and evidence-based health and drug data sources are available to community pharmacists to aid in these endeavors. There are a number of different types of health and medication data sources, but they can be broken down into three main categories: (1) product-specific medication information sources based on manufacturer provided information approved by regulatory agencies (for example, summaries of product characteristics and package leaflets within the European Union); (2) electronic heath and medication data information systems that combine information from various databases to aid in clinical

medication reviews; and (3) current care guidelines and other mechanistic descriptions of how to best administer a drug[27].

Community pharmacy in Finland draw on the same extensive network of health and drug databases utilized by hospitals and clinics. Finland's undergraduate pharmacy program includes an internship requirement, during which students apply what they've learned in the classroom to real-world problems in health and medicine. It is unclear, however, if these initiatives will actually result in students utilizing health and prescription data sources during the internship, which would better prepare them for using these sources actively after graduation. The purpose of this research was to catalog the health and drug information resources that pharmacy students in Finland have access to and actually utilize during their initial practicum experiences in community pharmacies. As digitization in healthcare will drastically alter the working habits of all healthcare workers, including community pharmacists, this study's findings have global relevance even though they were done in Finland[28].

### 2.1.2 Overview of Data Processing Practices

A When used as part of a larger health care infrastructure, health data can help both individuals and communities enjoy better health outcomes. A management information system, in other words. The term "management data system" has been used in many different contexts, but one of the more thorough definitions is "a system that provides specific information support to the decision making process at each level of an organization"[29]. With the available resources, the health data structure should generate the relevant data for use in decision-making at all levels of the healthcare system. To achieve this goal, a health system must have mechanisms in place for gathering, analyzing, and sharing data. When it comes to an individual's health, "Electronic Health Data" refers to the comprehensive electronic record of information created and gathered

cumulatively across multiple health care organizations and managed and consulted by licensed clinicians and staff involved in the individual's health and care. When someone receives information, they get insight into the world. Data is any information that has been entered into a computer by its owner.

Raw input is known as data, and the result of processing this data is known as information. Nowadays, data is stored in a wide variety of devices and presented in a wide variety of formats. It's crucial to have ready access to relevant data at the proper moment and in a well-organized style. Increases in health funding in recent years, such as those provided by the Global Fund to Fight AIDS, Tuberculosis, and Malaria, have contributed to a rising demand for high-quality health data[30]. Performance-based disbursement systems necessitate frequent monitoring of short-term programme outputs (such as improvements in service provision and the number of people using such services) in the context of such global initiatives, and reporting requirements for countries are being increased as a result. Improvements in life expectancy and quality require better reporting so that important international initiatives like the Millennium Development Goals may be tracked[31].

However, data needs arising from worldwide and disease-specific initiatives tend to center on specific indicators and do not automatically translate into constructing systems that suit the objectives of both countries and the international community. Inadequate resources have been allocated to developing efficient health information systems capable of producing data on the complete spectrum of health-related concerns, making it impossible to meet the current spike in demand for health data. Improving the efficiency of a company's healthcare systems is greatly aided by meticulous data management. Health care workers may see where their systems are lacking, make modifications, and monitor results by collecting, analyzing, interpreting, and acting on data for specified performance measures. Information on how to collect, analyze,

evaluate, and act on data for a given performance measurement is provided in this module, along with guidance on how to better comprehend the connection between quality improvement and data management[32].

Health data management systems have many uses in healthcare settings but are difficult to adopt in many low-income nations. For example, hospitals are better equipped to run their day-to-day operations with the help of electronic health data management systems, which benefit society as a whole[33]. Professionals in the field of health information management are well-versed in collecting and cataloging data for a wide range of purposes, including but not limited to disease severity, meaningful use, pay-for-performance, data registries, and data mapping. In addition to ensuring data is available when needed, health information professionals coordinate data collection, analyze data, and communicate findings to promote and stimulate data use. Involving users in the conversation for the design and execution of patient health record management increases the likelihood of a successful adaptation and rollout. EMR systems have been a boon to developing countries like India, Kenya, and Haiti by improving accuracy, efficiency, and overall cost[33].

On the other hand, the benefits of efficient management of health record systems are strongly dependent on the systems' ability to be successfully implemented. As a result, there is a pressing need to do research into what aspects of the health data management system may be enhanced in order to make it more efficient and flexible. Studies have indicated that the effectiveness of a new system's integration into everyday workflow is reliant on how well the culture of the workplace promotes quality and innovation. This is particularly important for the health data management system. There are cultural obstacles to the introduction of systems in hospitals, and it has been established that 77 percent of practices that do not have an electronic health record are opposed to adopting them. Another 72% of physicians were of the opinion that transitioning

to an electronic system would result in frequent downtime. Another 64% were of the opinion that the system would increase the amount of labor time that the physicians put in, and 60% were of the opinion that they lacked sufficient computer skills. Knowledge on the quality of healthcare data and its fitness for appropriate use in all of its intended purposes is the primary outcome of data quality management (DQM), which stands for "data quality management."[34].

Data application, collecting, analysis, and warehousing are some of the DQM tasks. DQM functions involve continual quality improvement for data quality throughout the company (all data in all healthcare settings). HIM professionals are not unfamiliar with the skills and roles associated with DQM. However, as the use of health information technology becomes more ubiquitous, data are being shared and repurposed in new and novel ways, which makes it more necessary than ever before to maintain a high level of data quality [35]. According to the relevant literature, each requester has their own particular way of looking for and collecting data. The processes of data gathering, analysis, and storage are rarely lightning fast. For example, large data sets are typically inaccessible; the quality of the data is frequently subpar; the requirements for centrally cleaning and standardizing the data may delay the beginning of analysis; there is almost no orderly method for reporting findings back to the people who hold the data; and decision-makers can very rarely obtain or make use of timely, high-quality information. The way that software is designed and the techniques that are used to populate data can both have an impact on the quality of the data that is collected. The automated populating of data comes from a variety of sources, including instruments used in clinical labs and devices used to monitor vital signs, such as blood pressure cuffs. Regular checks on all automated sources are required to confirm that the appropriate calibration has been achieved. In a similar vein, any staff that manually enters data ought to be educated on how to enter the data appropriately and monitored for quality assurance. One example of this would be registrars entering patient demographic data at the point of service. When it comes to the health industry, fragmentation causes data collecting

activities to be slow, expensive, burdensome, and redundant. Traditional techniques of data aggregation and dissemination present a great deal of difficulty for both researchers and the sources of the data.

Data are everywhere, and the input of data is necessary for making decisions that are informative. Elements of data will be utilized within a health institution as part of ongoing attempts to improve quality of care for patients as well as to enhance patient care strategically. Filling out forms, tally sheets, and registers, gathering data to compile into aggregated reports and statistics, and reporting health data from lower levels of the health information system to higher levels are all aspects of working with data and information within the context of the health information system. The majority of health workers are expected to participate in these activities as an integral part of their jobs. Therefore, health information systems have a tendency to be firmly ingrained in social work practices, and they are nearly impossible to disentangle from the social environment of which they are a part [36]. Data must be accurate, reliable, and organized in such a way that they can be understood and health information can be retrieved. This is true whether the data are being collected for the purpose of storing them in a paper medical/health record, in a computer-based or electronic patient record, or for specific registries. The first thing that has to be done is to figure out what kinds of data are required and how they are going to be gathered. When data are not collected in a logical order, and when the instrument that is used to collect the data is not up to par, this results in poor data collection.[37].

Investing in the development of efficient health information systems would have multiple benefits, including enabling decision-makers at all levels to detect and control emerging and endemic health problems; monitoring progress towards health goals; promoting equity; empowering individuals and communities with timely and understandable health-related

information; driving improvements in service quality; strengthening the evidence base for effective health policies; and allowing electronic health records. A concerted effort on the worldwide level is going to be necessary if we are going to be successful in improving health information systems at the national and sub-national levels. In contrast to the situation in wealthy nations, the integration of health information and information technology is not nearly as advanced in Kenya. The important hurdles that still need to be overcome are the high levels of IT illiteracy as well as the restricted availability of the necessary skills and equipment at the various levels. Therefore, even though the implementation of ICT is something to strive towards, the framework will place an emphasis on particular ways of producing and making use of health information that are applicable to the Kenyan setting. It takes a considerable portion of the time that health care professionals spend on the job to collect vast amounts of client and patient data; however, this data is rarely examined and put to use at the time that it is collected. The only thing that health workers do is collect aggregate data, which they then faithfully transmit to the higher level[38].

At the level at which the data is acquired, this information is almost never used to guide any kind of local action. Despite the fact that an HIS is primarily intended to facilitate the operations of various levels of health system managers, very little information from the data that has been collected ever makes its way to those responsible for managing the health system. This could be explained, at least in part, by the fact that information users were not involved in the design of these systems. Although the fundamental data collection and reporting skills are in place, there is very little attention paid to the quality of the data, and staff members lack the self-assessment skills and "epidemiological thinking" necessary for the analysis, interpretation, and application of information in the service of taking action. In addition, even when information users are involved, they frequently make data requests without being aware of the restrictions or obstacles

that are experienced by the providers in order to supply all of the information that is expected. It is a persistent issue because there is not a unified plan for the collection of data, which causes data collecting units and health care providers to engage in unnecessary duplication of effort and unhealthy rivalry. A significant portion of the data that is being produced by HIS suffers from a variety of issues, including low quality, incompleteness, inconsistency, and a lack of timeliness. Only the reasons for which medical data was collected, as well as any additional purposes approved by law or consented to by the data subject, shall be utilized to make use of the data once it has been obtained. It is imperative that the goals behind the collection of health data be made crystal apparent. Because of the demand for timely information that is accurate and comprehensive on the care and treatment of patients, the profession of Health Information Management (HIM) was established in Kenya. This allowed for evidence-based decision making within the health sector[39].

HIM professionals like their other colleagues within the health sector need to be regulated in order to ensure that they operate professionally. Data is a representation of facts or concepts or instructions in a formalized manner, suitable for communication, interpretation or processing by manual or electronic means in a health institution[40]. At the level at which the data is acquired, this information is almost never used to guide any kind of local action. Despite the fact that an HIS is primarily intended to facilitate the operations of various levels of health system managers, very little information from the data that has been collected ever makes its way to those responsible for managing the health system. This could be explained, at least in part, by the fact that information users were not involved in the design of these systems. Although the fundamental data collection and reporting skills are in place, there is very little attention paid to the quality of the data, and staff members lack the self-assessment skills and "epidemiological thinking" necessary for the analysis, interpretation, and application of information in the service

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A lack of adequate access to high-quality health information is responsible for the loss of countless lives all across the world. The availability of data that is accurate, current, and properly evaluated is directly linked to the quality of a person's health as well as the quality of the healthcare system as a whole, as well as the provision of individual treatment and the comprehension and management of overall health systems. The consolidation of existing health information networks is quickly becoming an essential component of global health policy. A lack of regularity in the data may make it difficult to enter the data. This suggests that it will be difficult to find solutions to issues connected to the quality of health care data in the absence of preset criteria and uniform data sets. The collection of data may also have an effect on the quality of the data if the forms used to collect the data are not well designed. If the forms are not well designed, the collection of data may result in data of poor quality. Some doctors have difficulty

recording data in a way that is clear and concise, which results in inaccurate information as a result of this difficulty, which is another reason of poor data quality. Abbreviations that are not standard are frequently used by the medical staff, and if a patient has been discharged from the facility or is no longer in need of treatment, the medical staff frequently claims that they are "too busy" to finish the patient's medical record. In a nutshell, a significant contributor to the low quality of the data is the minimal education of the medical professionals on the documentation requirements of data input[42].

There are restrictions on the transmission of information from one section of the facility to another, and as a result, the information that is being transmitted from the laboratory to the ward or a clinic may not contain the appropriate patient's name or their medical or health record number. Because of inaccuracies of this nature, it is impossible to verify that each particular patient's medical record contains all of the information that pertains to that patient. When moving information from one department to another, or from a hospital to a clinic or assistance station, the transfer of information is frequently sluggish, and sometimes information is lost altogether. Individuals in many regions of the developing world are unable to gain access to necessary health care, which in turn slows progress toward achieving the health-related United Nations Millennium Development Goals. The first step in effective information management is entering data into a centralized database so that it may be retrieved and used at a later time. On the other hand, the majority of developing nations do not possess a health information management system nor do they have skilled employees to carry out data entry duties. Discussions about bringing information technologies to health care in poor countries have, up until very recently, centered on the idea of replacing the widespread use of paper-based systems with computerized ones. According to the findings of this study, the quality of health care data and statistical reports has come under intense scrutiny in recent years, regardless of whether they come from a hospital,

health center, or a clinic located in a more remote location. As a result, all employees of health care services, including clerical staff, health professionals, administrators, and health information managers, need to acquire an in-depth knowledge and comprehension of the major components of data quality as well as the needs for ongoing data entry and improvement in order to do their duties effectively. This is due to the fact that erroneous health information can have a negative impact on a person's ability to receive adequate medical care, to obtain insurance, and to find gainful employment. It is of the utmost importance to preserve the honesty and accuracy of patient medical records in light of the ongoing trend toward the digitization of health records and the expanding role played by health information exchanges (HIEs) in the process of information sharing across organizations[43].

The primary objective of health information exchanges, or HIEs, is to improve the overall quality of care provided to patients while also reducing the amount of time spent on administrative tasks. The capacity to link (match) several, separate records that pertain to a single individual is essential to the accomplishment of this objective.

Data about people's health are gathered all around the world from a broad variety of sources for a number of diverse applications, including the secondary use for health monitoring (HM), public health surveillance, health system performance assessment (HSPA), and health research in general. HM refers to the performance and analysis of measurements that are carried out on an irregular or episodic basis for the purpose of identifying shifts in the health status of populations or in the physical or social setting. Population An crucial component of public health is health management, which refers to the systematic, institutionalized, and ongoing generation and transmission of information and knowledge regarding the health status of a population. Public health surveillance can be defined as the ongoing systematic collection, analysis, and interpretation of health data, which is essential to the planning, implementation, and evaluation of public health practice, closely integrated to the dissemination of these data to those who need

to know, and linked to prevention and control. In other words, surveillance is an essential part of planning, implementing, and evaluating public health practice[44].

The health of a nation as a whole can be in large part gauged by the efficiency of its healthcare system. The Health System Performance Assessment (HSPA) aims to track, analyze, and disseminate information about how well the health care system serves its intended purpose of improving people's health, accommodating their unique preferences and requirements, safeguarding their finances, and making the most efficient use of available resources. Additional requirements that a healthcare system should fulfill include access equity, efficiency, quality, safety, and resource allocation effectiveness. The preceding phrase detailed these requirements. When it comes to global health monitoring, public health surveillance, and HSPA, data collected by international organizations like the WHO, OECD, and Eurostat aren't always readily available in their respective databases. This restricts the potential of such databases for research, policymaking, international benchmarking and comparisons, and the sharing of best practices between nations45. The ability to compare study results across time and space requires that those results be comparable. Variations in indicator definitions, data gathering techniques and tools, and the use of different taxonomies sometimes impede comparability. It is possible to guarantee that study outcomes are comparable by standardizing data gathering methods and quality evaluation systems. Metadata standardization is particularly important in health information systems because of the importance of describing health data consistently. Metadata facilitates data comparison, access to public information, and re-use. Metadata can be defined as "explanatory texts documenting statistical data and providing summary information on definitions of populations, objects, variables, as well as the methodology and quality, and the statistical production process in general[45].

Three different approaches were used to gather data on the hospital admission date, discharge date, and discharge destination from a total of five research assistants with backgrounds in allied health. Before beginning the data collection process, a hospital researcher provided on-site training to each of the research assistants. a. Observational data that were manually collected by four research assistants from ward-based sources comprising nursing handover records, paper-based inpatient medical records, paper-based ward discharge/transfer records, and verbal handover from ward staff based on the preceding 24 hours. This method of data collecting was a pragmatic approach that was meant to emulate the way that these data would be collected in a major clinical trial with limited resources. The nurse in charge ensured that the nursing handover records were kept current on a daily basis. The ward administrative staff updated the transfer records constantly from 7:30 in the morning until 2:00 in the evening Monday through Friday and from 7:30 in the morning until 1300 in the afternoon on Saturdays. The nursing staff was responsible for updating the records during all other hours. b. Extraction of retrospective data utilizing administrative information from an electronic patient management program, performed by a single research assistant.

Admission and discharge information is entered into i.PM by administrative personnel between the hours of 07:30 and 2000 GMT Monday through Friday and between 07:30 and 1300 GMT on Saturdays. Nursing staff are responsible for entering information during all other hours. This information comprises the date, time, and destination of hospital discharge, in addition to the hospital admittance date and time, and hospital discharge. c. A retrospective examination of digitized hospital medical records by two research assistants after the patient was discharged from the hospital. Within the first 48 hours after a patient is discharged from the hospital, the health record administration personnel will routinely scan all of the paper-based inpatient medical data to create an integrated digital record. After then, one may conduct an electronic

evaluation of this record. The method of data gathering that was deemed to be the gold standard for the objectives of this research project was the retrospective evaluation of scanned inpatient medical records. This justification is based on the consideration of the medico-legal record of the patient admission as the primary source of information, and it has previously been used as a gold standard measure when assessing a variety of other outcomes, such as diagnostic accuracy and rates of adverse events, but not for the length of stay in the hospital or the discharge destination[46].

Although there are some subtle distinctions between the two terms, electronic medical records (EMRs), which are also frequently referred to as electronic health records (EHRs), are a significant contributor to clinical data. Electronic medical records, sometimes known as EMRs, are computerized medical information systems that gather, store, and display information about patients. They are methods for producing recordings that are readable and well-organized, as well as for gaining access to clinical information regarding specific patients. Electronic medical records (EMRs) have been hailed as an effective method for lowering the incidence of medical mistakes and fostering better information exchange among practitioners. However, there are a number of obstacles that prevent widespread adoption of EMRs. These include a lack of computer skills on the part of physicians, a lack of time, money, and trust in vendors, as well as security issues. Using a framework for the methodical adoption of EMR can help to reduce the impact of such impediments, at least to some degree. On the other hand, one must ensure that their expectations regarding the utilization of EHRs are in line with the realities of the situation by taking into account the fact that even nations with relatively high rates of EHR penetration have only had limited success in making use of EHR data for the betterment of population health[47]. It is still up for dispute how successful electronic medical records (EMRs) are at effectively improving the quality of care and the safety of patients. Electronic medical records (EMRs) include a variety of data sources that are useful for data science. Data that are directly

linked to a person's health status, such as laboratory values (which are tabular data), medical imaging (which is audiovisual data), or written comments from doctors (which might be semi-structured or free text), are the data that stand out the most. Data that can be collected from computerized physician order entry systems, clinical decision support systems, or scheduling systems are not as readily apparent but are certainly not any less valuable. The latter are primarily concerned with the processes involved in providing medical treatment; these procedures will be discussed in later chapters on operational excellence and value-based healthcare.

The acronym "laboratory information (management) system" (abbreviated as "LIMS") refers to a piece of software that is used in clinical laboratories to capture, manage, and save data. Historically, the primary function of a laboratory information system (LIS) has been to send orders for laboratory tests to laboratory apparatus, keep track of those orders, and then record the results, often in a database that users can search. By handling and reporting crucial data regarding "the status of infection, immunology, and care and treatment status of patients," the standard LIS has provided assistance for the operations of public health institutions (such hospitals and clinics) and the labs that are affiliated with those institutions. Radiology information systems (RIS) were first developed considerably earlier than electronic medical records (EMRs) in order to facilitate effective ordering and scheduling. Later on, RIS were combined with picture archiving and communication systems (PACS) in order to facilitate enhanced efficiency in the workflow of radiology departments. For instance, because to this integration, radiologist workdays were shortened by an average of 68 minutes, and fewer errors were left uncorrected or overlooked. The Patient Archival and Communication System (PACS) will eventually be replaced by a Vendor Neutral Archive (VNA), which can be used for more

than just radiology imaging (for example, even surgical video recordings or dermatology pictures)[48].

Another important source of information are the systems in use by external care and cure organizations, such as general practitioners. These systems are expected to have better integration or communication with hospitals' EMRs which would facilitate data exchange and provide new approaches for a more complete overview of a patient's individual journey including data collection at different time points and in different healthcare settings.

One way to help ensure patients get the care they need is to improve data analysis and reporting. Lack of understanding the requirement for accuracy and completeness in the processing of health records may be hampered by the limited education of processing workers. The reliability of their data will suffer if they are not given adequate training. Inadequate preparation on the part of administrative personnel to guarantee the existence of data quality control programmes. Finally, inaccurate information is reported for action due to data discrepancies resulting from errors at the stage of collection and planning[49].

Big data describes the vast volumes and variety of data being produced at breakneck speeds. Most of the time, data from multiple sources is needed to enhance consumer services rather than to optimize client usage. Large data sets, such as those generated by healthcare and biomedical research, follow the same pattern. Managing the vast quantities of data involved is the biggest challenge posed by big data. The data must be preserved in a file format that is both easy to read and easy to access before they can be made available to the scientific community. This will ensure the highest quality of analysis. In the context of healthcare data, the implementation of cutting-edge computing tools, protocols, and hardware in a clinical setting provides a considerable extra challenge. This is a really difficult obstacle to overcome. The goal cannot be

reached without the combined efforts of experts in fields as diverse as biology, IT, statistics, and mathematics. The collected data from the sensors can be made available on a cloud server with built-in software for analyzing the data created by the sensor manufacturers. These instruments would have data mining and machine learning capabilities developed by AI experts to help turn the information stored as data into knowledge. After it is implemented, it will improve the efficiency of gathering, storing, analyzing, and visualizing healthcare data in massive quantities.

The major goal is to convey this complex data in an acceptable way through annotation, integration, and improved readability. Without this kind of context, healthcare statistics remain impenetrable, and biomedical researchers may never make any forward. Finally, the visualization tools developed by computer graphics designers can effectively present this fresh information. The heterogeneity of the data is just one of the obstacles that must be overcome in big data analysis. Due to its massive scale and extremely heterogeneous nature, big data in the healthcare industry is generally less informative when evaluated with conventional methods. In order to run the software framework that facilitates the analysis of massive amounts of data, most organizations opt to use clusters of powerful computers that are available via grid computing infrastructures. Cloud computing is one such solution that uses virtualized storage technology and provides dependable services. In addition to its high levels of stability, scalability, and autonomy, it also provides ubiquitous access, dynamic resource discovery, and the ability to compose. These platforms can act as a data sink to take in information from all of the sensors all over a building, a data cruncher to interpret that information, and a visualization tool to present it to the user in an easily digestible format on the web[51].

Using the services of mobile edge computing cloudlets and fog computing, big data processing and analytics can be performed closer to the data source in the Internet of Things (IoT). This is made possible by the use of advanced algorithms. A programming language that is suitable for

working on big data (such as Python, R, or other languages) could be used to write such algorithms or software. As a result, a solid understanding of both biology and information technology is required.[52].

In the field of medicine, patient data may include recorded signals such as electrocardiograms (ECGs), photographs, and videos of the patient. The conversion of such healthcare data into EHRs has scarcely been accomplished by the providers of healthcare. The technique of translating static photographs into text that can be read by machines is now being worked on as part of ongoing efforts to digitize patient histories derived from notes written before the advent of electronic health records (EHR). For instance, optical character recognition (OCR) software is one option that can recognize handwriting in addition to computer fonts and push digitization. Another method that can do this is push digitization. Such unstructured and structured healthcare databases provide an untapped richness of information that can be harnessed using advanced AI systems to draw vital actionable insights in the context of patient care. These insights can improve the quality of care that patients receive. In point of fact, artificial intelligence has taken over as the method of choice for use in big data applications within the medical field. This clever approach has swiftly carved out a special place for itself in the process of deciding how diseases should be diagnosed. Healthcare practitioners examine this data using the right machine learning algorithms to look for specific problems. Machine learning can separate the organized information from the unstructured raw data[53].

BDA capability is defined as the ability to acquire, store, process and analyse large amounts of health data in various forms, and deliver meaningful information to users, which allows them to discover business values and insights in a timely fashion[54]. We propose four dimensions of BDA capability in healthcare: (1) data integration capability, (2) analytical capability, (3) predictive capability, and (4) data interpretation capability. Analytical capability refers to the ability to

drive decisions and actions through the extensive use of data and different analytical techniques based on the specific mechanisms used for analytics, thus addressing the various needs of users and other stakeholders. In healthcare, the use of analytical tools that can support core clinical operations and processes is particularly important as a means of increasing the quality of care[54].

The usage of healthcare analytical systems enables users to recognize patterns of treatment and uncover relationships from huge sets of healthcare records, so offering a more comprehensive perspective for evidence-based clinical practice. This type of analysis can uncover trends in patients that were previously undiscovered that are associated to readmissions to the hospital, which can promote a better balance between capacity and cost. Descriptive analytics, to give one example, is a powerful analytical method that has seen widespread application in BDA systems[55]. This method gives users the ability to comprehend past patient behaviors and how those behaviors might effect outcomes based on the information that is maintained in the hospital's database. This technique is typically used in a hospital context. Most crucially, the capability to analyze patient preferences enables hospitals to better understand the value of taking part in clinical trials and locate new prospective markets. Because data analysis has the potential to contribute to an increase in the effectiveness of healthcare delivery, we have included analytical competence as a fundamental feature of BDA capability.

The members of an organization who have an analytical mentality and contribute to deriving value from BDA are referred to as the organization's analytical personnel. The analytical staff fulfills a hybrid job that calls for a broad combination of technical and soft abilities as well as knowledge domains from across multiple disciplines. Researchers have conducted extensive research into the various skill sets required by analytical personnel. A researcher may classify members of the analytical staff as data scientists, data specialists, or big data analysts depending on the varying levels of data analysis expertise possessed by each individual. Data specialists not

only have a solid background in computer science, mathematics, and management, but they also understand how data is managed[56]. Data scientists understand how to extract answers to key questions from the tsunami of unstructured information that is available to them, whereas data specialists understand how to extract answers from unstructured information. Business analysts, who frequently have titles such as Chief Data Officer, are important executives in an organization. They are responsible for establishing solid governance to assure the quality of data, employing data-driven insights to make sound decisions, identifying business opportunities, and addressing business problems. Business analysts commonly hold titles such as Chief Data Officer.

Because erroneous interpretations of the reports that are created can lead to major lapses in judgment and judgments that are open to debate, having managers and staff who are skilled in the required professional analytic competencies is an essential component for the success of BDA. In point of fact, the ability of an organization's analytical personnel to comprehend not only the general business environment but also the particular organizational context of the data they deal with is crucial to the accomplishment of a BDA project. This comprehension is required on both a macro and micro level. Surprisingly little information regarding the role of the analytical personnel as an enabler of BDA success has been revealed in the existing body of research literature.

Because of its tremendous potential to provide high-quality images of anatomical structures in humans, medical imaging plays a significant role in modern healthcare. Because it can help with illness monitoring, treatment planning, and prognosis, effective image analysis can be valuable for doctors and medical researchers[57]. Magnetic resonance imaging (MRI), computerized tomography (CT), positron emission tomography (PET), and ultrasound (U/S) are the most common imaging modalities utilized to acquire a biological image. The ability to examine

human organs from the inside without causing harm to the patient has profound implications for medical practice. These advancements allow doctors to learn more about a patient's condition without having to physically open them up. However, observing such organs visually is only the first stage in the procedure. Biomedical image analysis's end goal is to derive quantitative information and draw inferences from photos that can shed much more light on a medical issue. Since this kind of study is essential to understanding biological systems and finding effective solutions to health problems, it has profound societal implications. But there are a lot of obstacles to overcome because the images are often different, complicated, and full of irregular shapes and noisy values. Research issues that occur while studying photos fall into several broad areas. These include object identification, image segmentation, image registration, and feature extraction. When these issues are fixed, it will be possible to generate useful analytical measurements that can be fed into other branches of healthcare data analytics.

In the field of medicine, sensor data is omnipresent, both in the present and for future research. Electrocardiogram (ECG) and electroencaphalogram (EEG) machines, for example, are sensors that collect impulses from different regions of the human body in order to provide medical data. These data collection tools are employed for both historical and real-time analysis[58]. In the setting of intensive care units (ICUs) and real-time remote monitoring of patients with specific medical conditions, real-time analysis may have the greatest impact. In any of these scenarios, the quantity of data to be processed can be significant. In a critical care unit (ICU), for instance, a sensor may collect information from hundreds of data sources, and alarms must be activated instantly. Big data frameworks and specialized hardware platforms are required for such applications. In remote monitoring applications, it is important to consider both immediate occurrences and longer-term patterns and treatment options. The exponential increase of sensor data has the potential to greatly improve medical care, but it also poses the problem of

information overload. This highlights the critical need for cutting-edge data analytics tools capable of turning massive datasets into actionable insights. In addition to improving the ability to observe patients' physiological signals and bring situational awareness to the bedside, these analytic approaches will shed light on the inefficiencies in the healthcare system that may be at the heart of rising costs. Sensor mining applications and systems in both clinical and non-clinical contexts, as well as the research hurdles connected with mining such data, are discussed.

The practice of measuring signals from biological sources, the origin of which rests in a variety of physiological processes, is known as biomedical signal analysis (or BSA for short). Electroneurograms (ENG), electromyograms (EMG), electrocardiograms (ECG), electroencephalograms (EEG), electrogastrograms (EGG), phonocardiograms (PCG), and other types of electrocardiograms and phonocardiograms are all examples of such signals. The examination of these signals is absolutely necessary in order to correctly diagnose the pathological conditions and select a suitable treatment plan. The state of the human body can be evaluated quantitatively or relatively by measuring physiological signals, and either method can provide useful information. These signals are obtained from a wide variety of sensors and transducers using either an intrusive method or a non-invasive one. These signals may be discrete or continuous, depending on the type of treatment administered or the degree of severity associated with a specific clinical condition. The low signal-to-noise ratio (SNR) and the interdependency of the physiological systems provide difficulties in the processing and interpretation of physiological signals. The signal data that is collected from the relevant medical instruments can frequently be extremely noisy, and it may at times be necessary to perform a substantial amount of preprocessing on the data. The development of a number of different signal processing algorithms has resulted in a notable increase in our level of comprehension

regarding the physiological processes. Filtering, the elimination of noise, and approaches that require less space all make use of a wide variety of ways[59].

More sophisticated analysis methods including dimensionality reduction techniques such as Principal Component Analysis (PCA), Singular Value Decomposition (SVD), and wavelet transformation have also been widely investigated in the literature. A broader overview of many of these techniques may also be found in. Time-series analysis methods are discussed in.

However, the nature of the causality between the genetic markers and the diseases has not been fully established despite the fact that a considerable number of diseases have been shown to have a genetic basis. For instance, it is well known that diabetes is a hereditary disease; nevertheless, the complete collection of genetic markers that predispose an individual to developing diabetes is not yet fully understood. In certain other instances, such as the blindness brought on by Stargardt disease, the genes that are involved have been identified, but not all of the probable mutations have been exhaustively uncovered. There is little question that a deeper comprehension of the connections that exist among the many genetic markers, mutations, and disease states has the potential to be of great assistance in the research and development of the many gene therapies that are needed to treat these diseases. One's primary focus should be on gaining an understanding of the kind of health-related questions that can be answered by doing data-driven research that involve in-silico analyses of genomic data. In addition, putting genetic discoveries into practice in the field of customized medicine is a very difficult endeavor that is still plagued by a great number of unresolved difficulties. For instance, the genomic landscapes of complex disorders like cancer are extremely intricate, which reveals a high order of variation amongst different people. When these problems are solved, a significant piece of the puzzle will have been assembled, and the idea of individualized medicine will be that much closer to being a reality. Recent developments in biotechnology have paved the way for the expedited production

of vast quantities of information in the fields of biology and medicine, as well as for the advancement of research in genomics. This has also led to previously unimaginable opportunities and expectations for the study of difficult issues in the field of life science on a genomic scale. For instance, recent developments in genomic technology have made it possible to investigate the entire genomic landscape of healthy persons for the purpose of diagnosing and treating complicated disorders[60].

Many of these study directions have already demonstrated promising outcomes in terms of creating new insights into the biology of human disease and to anticipate the tailored response of the individual to a certain treatment. These are two of the most important goals of medical research. Additionally, genetic data are frequently represented as either sequences or networks in models. Therefore, having a solid understanding of sequence mining and network mining techniques is necessary in order to operate in this subject. Several different data analytics-based solutions are currently in the process of being created in order to solve significant research problems in the medical field. These difficulties include the identification of disease biomarkers and treatment targets, as well as the prediction of clinical outcome. The evidence that may be found in the biomedical literature is utilized by a sizeable portion of the apps. The latter is abundant and has shown tremendous expansion throughout the course of time. In the field of biomedicine, applications that rely on evidence from scientific publications highlight the significance of the utilization of text mining tools for the long-term preservation, accessibility, and usage of digitally available resources. Text mining techniques and technologies provide innovative approaches to the application of new information finding techniques in the biomedical industry61. These tools provide researchers with effective means to search for, extract, combine, analyze, and summarize textual material, hence assisting researchers in the process of knowledge generation and discovery.

The trans disciplinary nature of the field presents one of the most significant obstacles to overcome in biomedical text mining. For instance, biologists will use brand names to describe chemical compounds, whereas scientists will typically use names that are IUPAC-compliant and therefore less ambiguous, or unambiguous descriptors such as International Chemical Identifiers. Text mining techniques are necessary in order to extract less precisely specified entities and their relations from published works of literature. The latter may be handled with cheminformatics tools, but the former cannot. In this scenario, the discovery of meaningful knowledge from unstructured databases is largely dependent on the application of entity and event extraction techniques. Text mining algorithms offer new potential for the efficient populating, updating, and integration of such datasets. This is necessary because the expense of curetting large databases is prohibitively expensive. Text mining provides additional advantages to the field of biomedical research by, among other things, correlating textual data to biomedical pathways, lowering the cost of validating expert knowledge, and producing hypotheses. This method offers a generic framework that may be used to find links that were not previously known to exist and improve the way that biomedical knowledge is organized.

The swift proliferation of various social media resources, such as social networking sites, blogs/microblogs, forums, question answering services, and online communities, has resulted in a wealth of information being made available on the general public's perspective on various facets of healthcare. Data from social media platforms can be mined for beneficial patterns and knowledge, which can then be applied to create helpful judgments about the health of populations and the monitoring of public health. The contributions made by diverse users of social media platforms can be mined for a substantial amount of information that pertains to the field of public health. The vast majority of individual posts and messages made on social media have very little informational value; nevertheless, the accumulation of millions of such posts and

messages can yield significant knowledge[62]. The amount of time needed to acquire such complicated data can be considerably cut down by doing an efficient analysis of these large amounts of information. Previous research on the use of social media analytics to the field of healthcare has concentrated on identifying aggregate health trends such as outbreaks of infectious diseases, discovering reports of bad drug interactions, and increasing interventional capacities for health-related activities. An investigation of the history of the content on social media can provide extremely helpful information regarding disease outbreaks. This is because the identification of disease outbreaks is frequently strongly reflected in the content of social media. When doing more in-depth analyses of topics like these pertaining to health, topic models are typically employed.

Online groups that bring together doctors and patients provide yet another avenue via which users of social media sites can gather information. Online forums are a significant source of knowledge regarding a variety of medical disorders because medical diseases tend to occur more frequently in certain individuals than in others. The fact that the data is frequently incorrect is one of the most difficult aspects of social media analysis. As a result, the findings need to be taken with extreme caution. The ability to make accurate clinical predictions is an essential part of today's medical system. A number of different prediction models have been the subject of substantial research and have been implemented in clinical practice with great success[63]. These kinds of models have had a significant effect, both in terms of the diagnosis and treatment of many diseases. The majority of successful supervised learning methods that have been utilized for clinical prediction tasks can be broken down into the following three categories: (i) Statistical methods including linear regression, logistic regression, and Bayesian models; (ii) Sophisticated methods in machine learning and data mining including decision trees and artificial neural networks; and (iii) Survival models that aim to predict survival outcomes. Discovering the

underlying relationship between covariate variables, also known as traits and features, and a dependent outcome variable is the primary emphasis of each of these methods. The outcomes that need to be predicted are the primary factor that should guide the selection of the model that will be applied to a specific healthcare situation. There are many different sorts of prediction models that have been offered in the research that have been done in order to deal with such a wide range of outcomes. Binary and continuous forms are examples of some of the most often occurring outcomes.

It is impossible to reason about or mine healthcare data without taking into account the temporal dimension because the data almost always contain information about the passage of time. There are two primary sources that contribute to the generation of temporal data in the healthcare industry. The first type is information from electronic health records (EHR), and the second type is information from sensors. The mining of the temporal dimension of EHR data is particularly promising because it may uncover patterns that enable a more detailed understanding of the appearance of disease, its development, and patients' responses to treatment. Because EHR data are distinguished from other types of data by their heterogeneity, sparsity, high dimensionality, and irregular time periods, conventional approaches are unable to adequately process this type of information. Data collected by sensors, as opposed to electronic health record data, are typically given in the form of numerical time series that are frequently and repeatedly monitored in time at a high frequency. These recordings include things like electrocardiograms (ECG), electroencephalograms (EEG), and a variety of other types of recordings of patients' electrical activity. Some examples of this type of data include physiological data gathered by regularly monitoring the patients. When compared to the longitudinal EHR data, which are often collected throughout the patient's whole lifetime, sensor data for a particular subject are measured over a considerably shorter period of time (generally several minutes to several days)[64].

Because EHR data and sensor data come from two very distinct sources, selecting the most effective temporal data mining methods for each type of data can be a challenge. EHR data are typically mined via temporal pattern mining methods. These approaches represent data instances (such as patients' records) as sequences of discrete events (such as diagnosis codes, procedures, etc.) and then attempt to locate and enumerate statistically important patterns that are inherent in the data. In this way, EHR data can be mined. On the other hand, sensor data are frequently studied by employing various signal processing and time-series analysis techniques (such as the wavelet transform, independent component analysis, and so on).[64].

In order to provide a better knowledge of diseases and to find patterns that could be affecting the clinical workflow, it is necessary to address the capacity to analyze and identify significant patterns in multimodal clinical data. This can be done by addressing the ability to analyze and identify meaningful patterns in multimodal clinical data. The strengths of human cognition, interactive interfaces, and data analytics that can assist the investigation of complicated datasets can be combined through the use of visual analytics, which gives a mechanism to do so. Visual analytics is a science that combines the integration of interactive visual interfaces with analytical approaches to construct systems that allow reasoning about and interpretation of complicated data[64]. This integration is done in order to create systems that can be used to develop new products. Because of the myriad of insights that may be gleaned from conducting such a study, visual analytics has become increasingly prevalent in numerous facets of healthcare data analysis. As more health-related information becomes available, it is becoming increasingly important to devise efficient methods of evaluating huge amounts of data by utilizing human–computer interaction and graphical user interfaces. This is because the amount of health-related data is rapidly growing. In general, it is helpful for humans to get unique insights when complex healthcare data is summed up in a way that can be easily understood by the reader. Clinicians are

frequently confronted with datasets that comprise hundreds of clinical characteristics as part of the evaluation process for many different diseases. When trying to synthesize the information and derive insights from the data, users face considerable hurdles brought on by the multimodal, noisy, heterogeneous, and temporal aspects of the clinical data.

Because healthcare companies are producing such a massive volume of information, there are now chances to build new interactive interfaces for the purpose of exploring large-scale databases, validating clinical data and coding systems, and increasing transparency inside various departments, hospitals, and organizations. While many of the visual methods can be immediately adapted from the data mining literature, a number of methods that are special to the healthcare domain have also been designed. These methods have been developed[65].

The nature of human diseases is fundamentally complex, and they are typically controlled by the intricate interaction of a number of various elements that lie beneath the disease's surface. These factors might range from genomic to clinical to behavioral to environmental in origin. Both clinicopathological and genomic databases represent, in a complimentary fashion, the myriad of effects that can be attributed to a wide variety of variables. It is absolutely necessary to construct integrative models that take into account both genomic and clinical factors simultaneously in order for these models to be able to incorporate the critical information that is included in both clinical and genomic data. These models can be of assistance in the design of efficient diagnostics, new treatments, and novel medications, bringing us one step closer to personalized medicine in the process. Because of this opportunity, a new field of integrative prediction models has begun to emerge. These models, which are referred to as clinico–genomic data integration, can be constructed by combining clinical data with genomic data. Genomic data refers to a patient's genomic information including SNPs, gene expression, protein, and metabolite profiles, whereas clinical data refers to a broad category comprising a patient's pathological, behavioral,

demographic, familial, environmental, and pharmacological histories. Clinical data also refers to the history of a patient's illness[66].

The majority of the time, the objective of the integrative study is biomarker discovery. This refers to the process of identifying the clinical and genomic factors that are associated with a specific disease phenotype, such as cancer vs. no cancer, tumor vs. normal tissue samples, or continuous variables such as the length of time a patient survives after undergoing a particular treatment. Even while the majority of work in healthcare data analytics is concentrated on the mining and analysis of data pertaining to patients, other information that can be used in this process includes scientific data and published literature. Techniques from the discipline of information retrieval (IR) are among the most prevalent methods utilized in the process of gaining access to these records. The area of information retrieval, sometimes known as IR, is concerned with the gathering, organization, and querying of knowledge-based information, which is typically characterized as information that is acquired and organized from observational or experimental research[67]. The implementation of IR systems is now practically present in every industry. It is believed that over eighty percent of people who use the Internet in the United States have done so in order to search for information pertaining to their own personal health, and the vast majority of medical professionals make use of the internet. The challenges faced by clinical and biomedical text mining are intricately connected to the models used for information retrieval. Finding the information that a user is looking for based on the criteria that he or she has specified is the primary goal of employing information retrieval. Typically, this will start with the formulation of a question to be sent to the IR system.

A search engine utilizes metadata to determine which content items best match a user's query. Indexing, which is the process of assigning metadata to the content, and retrieval, which is the process of the user entering the query and receiving relevant content, are the two primary

components of IR. Indexing is the process of assigning metadata to the content, and retrieval is the process of the user entering the query. The inverted index is the most well-known data structure that is used for retrieving information efficiently. Within this structure, each document has an identifier that is associated with it. After then, each word leads to a set of IDs for the documents. When conducting a search using keywords, a representation of this kind is especially helpful. In addition, once a search has been carried out, the procedures to rate the potentially vast number of results that have been retrieved are necessary. This is the case whether or not the search was successful. Over the course of the years, there have been a number of user-oriented assessments carried out. These evaluations have focused on users of biological information and have measured the search performance in clinical settings[68].

The phrase "a person's right and desire to control the disclosure of their personal health information" is typically considered as an adequate definition of privacy in the context of the healthcare industry.[69]. Data pertaining to the health of patients is considered to be of the highest confidentiality because it may contain information that could compromise individual participants. There are many different types of data, such as information on diseases or genomic information, which may be sensitive for a variety of reasons. It is frequently essential for medical organizations to have the capacity to share their data with statisticians who are knowledgeable in the subject in order to facilitate research in the field of medicine. The act of disclosing private medical information can result in significant financial savings. Concerns concerning the personal privacy of persons are warranted as a natural consequence of this development. In the realm of healthcare data analytics, one of the most significant difficulties is protecting the confidentiality of patients' personal information. The majority of approaches for protecting an individual's privacy result in a reduction in the accuracy of the data's representation, which compromises the ability to identify sensitive aspects of an individual. This can be accomplished in a few different

ways: by introducing noise into the sensitive property; by introducing noise into the characteristics that serve as identifying mechanisms; or by combining the two approaches. Evidently, the precision of the data representation needed to be sacrificed in order to complete this operation.

Therefore, protecting an individual's privacy almost always comes at the expense of some data utility being sacrificed. Therefore, the purpose of strategies that preserve privacy is to maximize the benefit that may be gained while sacrificing as little personal information as possible. Because of this, the amount of utility lost while maintaining a specific level of privacy is reduced to the greatest extent possible. Application of one or multiple privacy-preserving algorithm(s) to achieve the desired privacy level, post analysis of the utility of the processed data, and identification of an appropriate privacy metric and level for a given access setting and data characteristics are the major steps in privacy-preserving data publication algorithms. These steps include identification of an appropriate privacy metric and level for a given access setting and data characteristics. These three processes are repeated as often as necessary until the optimal levels of utility and privacy are simultaneously achieved.

A data store is a collection of data that is subject-oriented, integrated, non-volatile, and time-variable. Its purpose is to support the decisions that management makes. Granular information about the company is stored in the data warehouse. When viewed from a perspective that is more subject-oriented, traditional business operations systems are structured around the applications used by the corporation. Every variety of business has its own one-of-a-kind roster of topics to cover. In terms of the level of interest. The data warehouse receives input from a wide variety of different sources on a continual basis. The data is converted, reorganized, rearranged, and summarized as it is being input into the system. The end effect is that once data is stored in the data warehouse, it takes on a unified and consistent physical representation of the company. Data

is loaded into the warehouse, and it can be accessed, but it is not updated. In its place, the data in the data warehouse is placed into the warehouse in a manner that is both snapshot and static. When fresh changes take place in the future, a new snapshot record will be written. The data warehouse is updated with a complete history of the data as a result of this action. Many people believe that data warehousing is one of the most strategically significant breakthroughs that has taken place in the field of information processing in recent years. One of the reasons for this is that it is considered to be a part of the solution to the problem of too much information being available[70].

Data storage is a phenomenon that emerged as a result of the enormous amount of electronic data that has been saved in recent years and the pressing need to make use of that data in order to achieve objectives that go beyond the normal chores that are associated with everyday processing. In a typical scenario, a large hospital institution consists of multiple branches, and senior management are required to quantify and analyze the manner in which each branch contributes to the overall success of the worldwide organization. The database of the company keeps information in great detail on the activities carried out by the various departments that make up the company. In order to fulfill the requirements of the managers, individualized queries can be constructed to retrieve the necessary data. After carefully examining the relevant database catalogs, database managers need to begin by formulating the necessary query before moving on to the next step of the procedure. The query is then handled after that. Due to the vast amount of data, the intricacy of the query, and the concurrent effects of other regular workload queries on data, this can take a few hours. At long last, a report is compiled, and it is delivered to upper-level management in the form of a spreadsheet. Database designers learned a long time ago that such a strategy is almost never viable since it is exceedingly demanding in terms of time and resources, and it does not always produce the results that are sought. In addition, combining

analytical questions with normal transactional queries would definitely cause a slowdown in the system. This does not fulfill the requirements of users who conduct either sort of inquiry[71].

Although data science can assist us in organizing and standardizing hospital data, this alone will not be sufficient. This activity must therefore inherently require a significant amount of mobilization on the part of the health professionals who "produce" the data. Let there be no misunderstanding: the full potential of this massive amount of information is contingent not only on the vast number of highly varied data that is acquired at a rapid pace in hospitals, but also on the ability of those who produce the data to analyze it and then draw trustworthy conclusions from it. This question is referring to two aspects of the data that pertain to health: first, the structuring of the data (is it structured or is it not? Does this data benefit from a standardized structure that is based on a nomenclature or does it not?) and its quality (does the data fulfill quality requirements that enable us to state that it is interpretable and complete?). Does this data benefit from a standardized structure that is based on a terminology or does it not? It is impossible to be content with inaccurate or incomplete clinical data or medical imaging of poor quality; this would simply cause the AI algorithms to provide outcomes that are not very robust or to model incorrectly. Because of this dual requirement of data structuring and quality, an increasing number of hospitals have made the decision to develop their very own comprehensive clinical data warehouses, or to become a part of national, regional, or subregional networks that already have a DWH. These data warehouses contain all of the information that has resulted from the care that their patients have received[72].

Real-world evidence studies, which are carried out based on data gathered in current care practice outside of the traditional framework of clinical trials, require accurate data to assess medical or treatments outcomes[73]. Electronic Health Records (EHR) are increasingly being used for real-world evidence studies. Real-world evidence studies are defined as studies carried out

based on data collected in current care practice. Before carrying out this exploitation, it is necessary to find solutions to a number of issues, including those of a technical nature affecting the formatting and quality of the source data, as well as the interoperability of those data and their incorporation into these DWH. Patients in hospitals are cared for by multidisciplinary teams over the course of sometimes extended periods of time, which generates enormous volumes of data. The nature of health data is such that they are exceedingly varied in terms of typology and format. This is because there are so many various sources of data and so many different environments in which they are produced. There is a lot of diversity in the data since the data can originate from the same source but in many different formats. This contributes to the variety in the data. For instance, the textual data contained in a medical report might be presented in a variety of formats or discuss the same topic using a variety of phrasings. When discussing data in a more general sense, it is possible to differentiate between "unstructured,""semi-structured," and "structured" data. Textual data, for instance, can be found in hospitalization, consultation, anatomopathology, and multidisciplinary consultation meeting reports. This first form of data is by far the most prevalent, as it accounts for 80% of computerized patient data in health care institutions. One example of this sort of data is found in multidisciplinary consultation meetings. Algorithms based on natural language processing (NLP) can be utilized to evaluate unstructured materials at a high speed and with a high level of accuracy.

Images obtained from medical procedures are another type of unstructured data. It is important to highlight that despite the fact that this unstructured imaging data may be accompanied by information, which makes it possible to comprehend the context in which the data is formed, they are still considered to be unstructured imaging data. The Digital Imaging and Communications in Medicine (DICOM) standard was developed specifically for the purpose of fulfilling this function in the context of medical pictures. A sort of data that lies between

completely unstructured data and fully structured data is referred to as "semi-structured" data or partially structured data. These data can be characterized by qualities, which can make the process of arranging them easier. Data that has been encoded in a tag-based computer language, such as XML (Extensible Markup Language), is technically referred to as tag data. Examples of data that are semi-structured include medical questionnaires and any other document that is saved in the Clinical Document Architecture (CDA) format according to the HL7 (Health Level 7) standard[74].

Finally, data is said to be "structured" when it has been processed and formatted according to a clear data model. When structured data is described in a repository, it can be enhanced with semantics to make it easier to use or analyze. Interoperability issues arise due to the fact that this description can be standard and then either local or shared by numerous data producers. The Hospital Data's Temporal and Functional Purposes The passage of time is an integral part of data. Data that has been collected repeatedly might be displayed as sequences or series. For instance, a patient's physiological measurements fall within this category. Traditional biological analysis data, for instance, may benefit from temporal analysis in order to evaluate the change in biological parameters over time. These records are known as signal data since their characteristics are determined by the rate at which they were recorded. The concept of time can also encompass a broader field, such as the reconstruction of healthcare routes. Performing this task is not always easy because it requires working with unstructured data[75].

The data's quality is largely determined by the nature of its use, including the necessary structure, normalization, and standards. The "fitness for use" approach is based on this fundamental idea. It is possible to evaluate the quality of data by considering its many aspects[76]. Finding a happy medium between the quality of each of these elements is part of determining a data item's intrinsic quality so that it can be used to accomplish a specific research goal. Commonly

examined aspects of data quality include its completeness, accuracy, consistency, timeliness of production, and validity. In the context of secondary data reuse, it is important to keep in mind that purposes are identified after the fact. If data meet the minimal standards stated by the 'FAIR' principles (Foundable, Accessible, Interoperable, Reusable), regardless of the attributes to be decided by the subsequent use of the data, they can be assessed as being of 'sufficient' quality[75].

Improving data quality to allow for reuse after data production has occurred can be accomplished in a number of ways, including: creating quality monitoring measures all through the data integration process to guarantee that raw data is not degraded; and creating analysis methods to fix data quality issues (reconciliation, duplication, etc.). Upstream interventions, in which corrective actions are applied to the source applications, are also conceivable and are sometimes aided by the fact that the end users are also the data producers. To develop indicators for measuring and monitoring data quality, secondary reuse requires specifying the dimensions of interest in light of the anticipated applications. Massive health data can be defined in terms of the technology required to exploit them, just as they can be defined in terms of the "5 V's" of big data (volumetry, variability, veracity, velocity, and value). Relational databases, the traditional method of data storage and processing, are no longer adequate, necessitating the use of alternate storage and processing technologies (distributed calculations, supercomputers, etc.)[76].

The criteria of authenticity, velocity, and value are very application-specific, and so might apply to any kind of data. The concepts of variability and volumetry have varying meanings depending on the nature of the data being examined. Digital medical imaging and omics data, for instance, satisfy the volumetry condition but rarely the variability criterion. On the other hand, the volume of electronic data contained in a patient file is quite little even though it varies widely. Regardless of the context, data storage and analysis approaches will need to be modified to accommodate the enormous volumes of information being processed.

When it comes to a company's transaction information systems, a data storage is defined as a "centrally managed and easily accessible copy of data." To make it easier to do searches, research, and analysis on a population level, these data are compiled, cataloged, and arranged. Famously dubbed the "father of data warehousing," A data warehouse is "a subject-oriented, integrated, non-volatile, and time-variant collection of data in support of management's decisions," as one researcher puts it. The data is subject-oriented rather than application-oriented since it is arranged not by laboratories or imaging systems but by patients. The data is merged by definition and substance from a variety of operating systems. A data warehouse collects information from various sources and processes it into a form that can be analyzed. Data warehouses store data indefinitely, unlike operational systems which purge data when it is no longer required by a certain application. The ability to do historical analysis relies on the stability of the data. In contrast to operational systems, which only keep the most up-to-date version of the data, data warehouses maintain a history of the data and any changes that were made to it. Analyzing trends throughout time is made possible by time-variance. In the end, the data is for management improvement through increased insight into the business[77].

A data store can be recognized by its multiple characteristics. By definition, a data warehouse stores massive amounts of information, perhaps in the millions of gigabytes. The technology provides a look back in time, as it is capable of spanning 30 years or more. Data is taken from source systems like billing, registration, or scheduling, and then integrated using the technology. The analysis provided by a data warehouse encompasses a wide range of business procedures; for instance, it will compare data from a billing system with data from a scheduling system. A data repository facilitates inquisitive thinking. It sheds light on hitherto unexplored regions and hitherto unanticipated problems. Reports and metrics are the products of data storage. Data

warehouses necessitate the assistance of trained professionals at every stage, from data gathering to data transformation for querying and report generation[77].

A data repository's primary function is to provide decision-makers with appealing business intelligence that facilitates their ability to comprehend issues, identify opportunities, and evaluate results. The data warehouse's ability to serve this role depends on its ability to combine and transform internal and external data collected over time into present conditions. To this end, data storage serves as the tool via which decision-makers can access and apply pertinent information in order to forecast and evaluate the long-term effects of their choices[77].

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[78].

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[78]. 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[79].

It is necessary to make available a set of tools for analysis and reporting that make use of the most recent technology and have as little duplication as possible in order to satisfy the information requirements of the end-users. Queries written in Structured Query Language (SQL) are run on an ad hoc basis and need the use of particular interfaces. The term "slice and dice" refers to the process of using on-line analytical processing, or OLAP, to process huge amounts of data. OLAP also offers analysts with an interface to alter different views and levels of aggregation. The selection and presentation of individualized reports can be accomplished using online interfaces using web reporting. Dashboards and scorecards both make use of graphical user interfaces to provide key indicators and quality measurements. These interfaces also allow users to drill down into top-level measures in order to evaluate the components of those measures. The goal of the approaches used in data mining is to uncover new and potentially relevant correlations and patterns in data. These patterns and correlations can be summarized, modeled, and clustered using algorithms. The data may be subjected to many types of statistical analysis, such as measures of central tendency, analysis of variance, regression, and time series analysis. Geographic Information Systems (GIS) provide geographic displays of data and can be used for a variety of purposes, including the analysis of locations where additional resources are required for particular goods and services, as well as the demonstration of geographical differences in distribution or consumption patterns [80].

If the predicted benefits of data storage are expected to be relatively big, the system requires a substantial amount of financial and technological resources, in addition to qualified labor and

sufficient amounts of time. Due to the fact that it encompasses a complete organization, it is affected by a wide variety of human and organizational elements. Because of its dependence on preexisting source systems, the quality of the output it produces is at risk. Furthermore, the fact that this output is in the form of reports and metrics that are used for decision support means that its use might have a variety of negative ramifications, some of which could be extremely serious. When applied to the healthcare industry, data warehousing adds another layer of complexity to an already complicated process. The data that is found in the medical industry is both more extensive and diverse than the data that is found in any other economic sector. In order to cover all parts of the care process, the data storage must address topics as different as clinical research, treatment effectiveness, financial analysis, and customer relationship[81].

In spite of the fact that numerous pieces of published research praise the benefits of health data warehouses, there is very little evidence to support these claims. Even when the scope of the review was broadened to include industries unrelated to healthcare, the current body of research turned up very few articles on the evaluation of data warehousing. Only particular aspects, such as the quality of the data and the system or the level of user satisfaction, have gotten more focus and benefited more from definitions and performance measures[82]. When it comes to knowledge that has been gained by the community of practitioners, anecdotal evidence is relied on the majority of the time. In addition, there are very few cases that can be identified that describe how an evaluation of the technology can be made, and these cases do not provide any insight into how an evaluation of this kind might be standardized. In place of evaluation concepts and methodologies, the idea of success is frequently used as a basis for assessing the system. The Critical Success Factors (CSFs) model is one such concept's practical application. CSFs, or critical success factors, are components that have been determined to be essential for an

organization or project to accomplish its goals and be a success. The inability to accomplish the goals connected to CSFs ultimately leads to the demise of the project or organization.

The CSFs were not used in the investigation at all. This strategy not only simplifies evaluations by reducing them to a black-and-white approach, but it also depends on ill-defined and debatable ideas. Even if data warehouses are successfully deployed within their allocated budgets, this does not guarantee that they will be put to their full potential. It is also possible for the opposite to be true, namely that the technology is lauded highly by users despite the fact that it is not extensively utilized. In other words, the identification of some CSFs does not require any empirical testing, and various procedures of measurement are utilized for the evaluation of some of the components. The concept of being successful has also been the focus of a significant amount of academic investigation. about the course of the past twenty years, academics have been mulling about how best to describe the achievement of success in information systems, along with the various components of achievement. The selection of their theoretical model as the basis for the study that is detailed in this dissertation was a conscious one. Despite the fact that its model and the empirical research that were undertaken in order to apply it helped generate a set of success determinants and measurements, there is not yet widespread agreement regarding what the idea of success implies. In the absence of such consensus, the usage of elements such as the actor for whom success is defined and rather his or her view can prevail within an organization continues. This is because there is no consensus on how success should be defined. Because of this, the evaluation of information systems is frequently neglected, and it is nearly hard to make meaningful comparisons between the various systems used by different businesses.[83].

The storage of data has as its primary objective the facilitation of decision making, that is, the improvement of decision making quality by the provision of information that is both pertinent

and timely in an effort to reduce the uncertainty that is inherent in decision making. Through the use of a laboratory experiment that simulated a marketing environment in which decisions on sales force deployment have to be made based on trend analyses, research has been carried out to investigate and contrast enterprise-wide data warehouses with standard databases that only store a portion of data[84]. The findings of the study suggested that storing data in its entirety greatly enhanced choice performance, whereas storing data in its entirety did not improve decision performance. In addition, the findings of the study demonstrated that, in comparison to conventional databases, partial data warehousing did not result in any noticeable improvements. The contribution of the research is extremely valuable due to the fact that it is one of the very few studies that examines the effects of data warehousing on the performance of decision-making. On the other hand, the experiment was conducted with stand-in managers, in the form of MBA students. The amount of data involved was rather low, and the scope was limited to only a few distinct jobs. As a result, the findings cannot be generalized outside of the sphere of marketing, nor can they be extended to professional decision makers or to activities that require the analysis of bigger volumes of transactional data84. Moreover, the findings cannot be extended to tasks that require the analysis of large volumes of transactional data.[84].

Software testing and information system evaluation share similar methodological techniques despite serving different aims. The purpose of the testing phase of the software development life cycle is to reveal hidden flaws in the code and identify potential threats to the project. Thus, techniques are employed to discover flaws and defects during the course of the application's execution. Data warehouse testing is more all-encompassing than software testing, which focuses primarily on the functionality of the code itself. The correctness and value of the data and the information offered to users are both considered. Due to the ever-evolving nature of data storage projects, testing is not limited to the phases preceding deployment but continues even after the

release of the system. Conceptual and logical schemas, as well as data repositories, need to be tested; the ETL process (back-end testing) and reporting and analysis technologies (front-end testing) must also be thoroughly examined. Both ensure that the information available through reporting systems is accurate and consistent with the information used to fill the data warehouse. Functional testing is used to ensure the product meets the needs of the business; usability testing gauges how simple it is to use; performance testing guarantees the tech works well under typical usage; stress testing measures how well it handles peak usage; recovery testing gauges how well it handles crashes and hardware failures; security testing ensures data is safe; and regression testing checks for bugs in previously released versions[85].

Supporting decision-making activities and setting up an architecture for ad hoc exploration of very big data intake are only two of the many useful tasks carried out by healthcare data storage. Rather than relying solely on database programmers to construct queries, decision makers should be able to conduct various inquiries with browsing tools. Due to the importance placed on data accessibility for end users, an easily comprehensible database design that provides an easy foundation for browsing the data is essential. Many parts of a data warehouse benefit from being organized according to the dimensional model, also known as the star schema. The numeric information found in the center fact table of the star schema is perfect for use in executive summaries. Rich query environments are made possible by the fact table's radial relationship to the dimension tables. Dimensions such as time and place can be used to uniquely identify a series of numerical measurements within this logical data cube's confines. Coarse-grained data used in generic report development is kept apart from fine-grained data that describes specific events, such hospital discharges. All sorts of reporting needs and efficiency targets can be met by combining the data warehouse's three tiers of aggregation. Core reports, like comparisons between a target county and peer counties, are generated from reporting tables at the top of the

pyramid, which include highly aggregated data. To facilitate easy, community-wide Internet access, these tables provide quick interactive response times when accessed via data browsing tools. True dimensional data warehouse features, such as interactive roll-up and drill-down procedures where facts are grouped at several levels for analysis, are provided by families of star schemas in the middle or aggregate level of the pyramid. These schemas feature well-thought-out dimensions that can be used by advanced data-browsing tools to back up OLAP methods of analysis. • The design keeps event-level or fine-grained data at the pyramid's base. Discharge information from Florida's over 200 hospitals is only one example of the types of data that must be reported. Because of the wealth of facts and dimensions that can be used for analysis and reporting, this information is kept at the transaction level[86].

The term "data output" describes the final usage of collected data. These specifics are compiled into data sets that are too huge and complex to be processed by common data software. Therefore, it is insufficient to deal with them because of the nature of the institutions and the large collection of patient data. Some of the issues that need to be addressed concern data analysis, collection, curation, search, sharing, storage, transfer, visualization, querying, updates, and privacy[87]. Analysis of hospitals that have recently implemented a comprehensive EHR system reveals that clinical and administrative executives have incorporated EHR adoption into strategic goals to integrate inpatient and outpatient care and provide a continuum of coordinated services. A successful rollout needed strong leadership, full engagement of clinical staff in design and implementation, mandatory staff training, and strict adherence to time and budget. Patient safety and quality improvement87 are aided by EHR systems in many ways, including the use of checklists, alerts, and predictive tools; embedded clinical guidelines that promote standardized, evidence-based practices; electronic prescribing and test-ordering that reduces

errors and redundancies; and discrete data fields that foster the use of performance dashboards and compliance reports[88].

Better communication and streamlined processes lead to increased patient flow, less repeat tests, faster responses to patient concerns, redirected transcription and claims staff, more complete charge collection, and federal incentive payments. Hospital and health system administrators used several strategies to demonstrate that implementing EHRs was a top priority. Each facility put a significant amount of money on technological assets like computers, servers, and IT workers. In addition to integrating EHRs in their own and affiliated clinics, integrated health systems also provided training for physicians. Most hospitals also offered training for local doctors who had admitting privileges but worked with a different electronic health record system in their offices.

Generate, transmit, and store healthcare information with the help of a wide variety of networking technologies, clinical databases, electronic /health records, and other specialized biomedical, administrative, and financial technologies. A patient's whole medical history can be found in an electronic health record that includes information from hospitals, clinics, emergency rooms, small offices, and multispecialty groups. This data is then electronically exchanged with other databases on a national and regional scale. In order to facilitate decision-making and decision-support, data from EHRs and regional registries are filtered into guidelines for prevention and treatment. Standards for both data transmission and data definition are crucial to the effective operation of the application system. Information from EHRs is processed and used in a way that enhances decision-making for cancer patients, leading to higher-quality care. Therefore, cancer treatment monitoring, management, and control using health information technology.

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[88].

Information on the selection of new technologies is often unstructured and imprecise, and the increasing number of technologies and the increasing complexity of those technologies further add to the problem. To name just a few examples, hardware and software costs, the availability of broadband and mobile networks, the development of user interfaces and applications in languages other than English, and ongoing maintenance costs are all better understood as general issues with the use of ICT. When thinking about new health care technologies, it is important to have a more holistic understanding of the broader social, political, and economic constraints, or'soft' barriers. In light of this glaring informational deficiency, the current research looks into the ways in which an efficient health information application system might boost health record management[88].

By analyzing consumer search, social content, and query activity, BDA 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. 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 127 countries89 are involved in GBD, which uses medical Big Data[89].

Globally, the 2015 report found that diarrhea was the greatest cause of death across all age groups and the leading cause of disability-adjusted life years (DALYs) because to its disproportionate impact on young children. In addition, BDA is frequently used to monitor drug safety, especially adverse drug reactions, and to locate vulnerable populations. Adverse drug reactions (ADRs) are defined as interventions associated to the use of a medical product that result in a detrimental or unpleasant reaction. In the field of medical administration, ADR can be used to justify the need for precautionary measures, targeted treatment, adjustments to dosing, or even product withdrawal. When possible ADRs are found among those who take the prescription, health departments or medical corporations can swiftly act with the help of Big Data. One researcher has suggested that Knowledge Discovery in Databases (KDD) is a better tool for detecting and evaluating ADR signals. A wide variety of data mining methods, including cluster analysis, link analysis, deviation detection, and disproportionality assessment, have already been applied to the problem of medication safety. With the rise of Big Data, researchers may now quickly and easily obtain first-hand ADR data from health social media platforms. Spontaneous

reporting of data on health social media platforms is significantly more abundant, open, and timely than ADRs recorded by healthcare professionals[89].

Big Data in biomedical informatics was predicted to increase rapidly in the coming years due to the advantages it offers and the success of medical research, especially in the ADR field. Without a shadow of a doubt, the era of data-medicine will usher in a health care system that is proactive, predictive, preventative, interactive, and patient-centered. In addition to the promising results in drug safety, Big Data has the potential to produce striking outcomes in the area of detecting vulnerable groups. A chance to uncover the statistical model of high-risk individuals is within the mountain of EHRs acquired through various medical procedures. The model's goal is to lower health care costs while maximizing the use of scarce health resources. It was proposed that the best way to put predictive medical systems to use is to first discover and then manage the data from six different practical use cases. Treatment optimization for diseases impacting multiple organ systems, high-cost patients, readmissions, triage, decompensation, adverse events, and more are all examples of use cases[89].

To construct a dynamic and up-to-date global infectious disease map, a researcher integrated new sources of data, such as social data, with pertinent environmental information. Humans can increase their understanding of infectious diseases, enhance their capacity for spatial triage, and issue outbreak alerts based on information provided by infectious disease risk maps. The arrogance of Big Data exists when its proponents mistakenly believe it can replace more established methods of data gathering and processing. It's a given that the results can be highly inaccurate, given that much Big Data cannot be analyzed to the level of scientific statistical rigor. Furthermore, medical algorithms tend to change often. They undergo a constant iteration of changes, though, making them dynamic. The mining of public medical patterns is just one application of big medical data, which can also be used to provide individualized treatment. The

current trend in healthcare is away from treating diseases and toward treating individuals. Decisions made by doctors in a disease-centered paradigm are based on their extensive training and experience as well as the results of numerous diagnostic procedures. Services provided in a patient-centered model are tailored to each patient's specific situation and values. When it comes to patient care, data drives the personalized model. This requires a medical model with a focus on the individual patient that can evaluate the link between individuals with comparable risk, lifestyle, and environmental profiles[90].

In light of these considerations, we built a system called CARE that use a collaborative filtering technique to identify shared characteristics among patients and generate unique illness profiles for accurate risk assessment. The primary difficulties were highlighted by a scholar, who took into account the data's variety, quality, volume, and velocity. The disparity in healthcare provision between wealthy and poor countries may worsen as a result of the rise of personalized treatment. As for the reasons for the slow shift from conventional to personalized medicine, they pointed to issues with data storage and processing, data integration and interpretation, as well as the individual and global economic relevance of the field[90].

## 2.2 Theoretical Framework

### 2.2.1 Theory of Human Service Delivery

The theory of human service delivery as postulated entails an understanding of how people work within systems to deliver services[91]. People are a resource unlike any other in that their value and availability can be difficult to quantify. Services are judged partly by subjective criteria, so understanding the quality that is provided by any service system can be tricky. Theorist attempt to understand how to build the best system for the best services through the following measures; intangibility, variability, limits and ideology.

Intangibility; Services by their very nature are intangible because they cannot be physically held by the customer. They are singular experiences that cannot be duplicated or transferred to another person. Providing a service to a customer requires a live person to communicate with her and attend to her requests. The designer of any technology that will interact with humans must prioritize their needs. The service providers must be kind and professional in their interactions with customers. Since services are one-off occurrences, they can have more variation than a company's other offerings. The gaps between service quality are going to widen. It takes significant work on the part of businesses to raise the bar on the reliability and consistency of their offerings. Constant efforts should be made to learn what customers want and how service may be enhanced. It's not uncommon to have to subtly implement a training plan.

Limits; Any company's ability to supply its services is inherently bounded by the size of its staff. There is a limit to how much work a single individual can handle in a particular period of time. It is common knowledge that adding more employees can improve the quality or output of almost any service. If you need a more complicated service, expect to pay more. Many human service delivery theorists emphasise the need for an organization's internal ideology to express a wider objective in order to motivate service providers and equip them with broad guidelines. People will be better equipped to handle a variety of issues and to explain their own efforts if they are presented with a more holistic picture. The most effective internal philosophies are those that motivate their followers.

In line with the theory, health information personnel have special understanding and expertise in an extensively renowned, organized body of education derived from a high level training. Therefore this theory is relevant to this study because it describe how health information personnel handle their service putting into consideration the job idea, it state of non-handling (intangible), how it varies from one hospital to the other and the limits to the work and expertise

connected to healthcare in terms of record keeping and human resource management technologies.

### 2.2.2 Data Processing Cycle

Data processing refers to the transforming raw data into meaningful output[92]. Data can be done manually using a pen and paper, mechanically using simple devices such as typewriter or electronically using modern data processing tools like computer. There are different stages of data processing cycle which include input storage (data collection, data capture, encoding, data transmission and data communication), processing stage (performing instruction and transform raw data into information), output stage (decoding and presenting data to user) and storage stage (storing data and retrieve data). Data collection involves getting the data/facts needed for processing from the point of its origin to the computer. Data input is the process whereby collected data is converted into machine-readable form by an input device, and send into the machine. Processing is the transformation of the input data to a more meaningful form (information) in the CPU while output is the production of the required information which may be input in future.

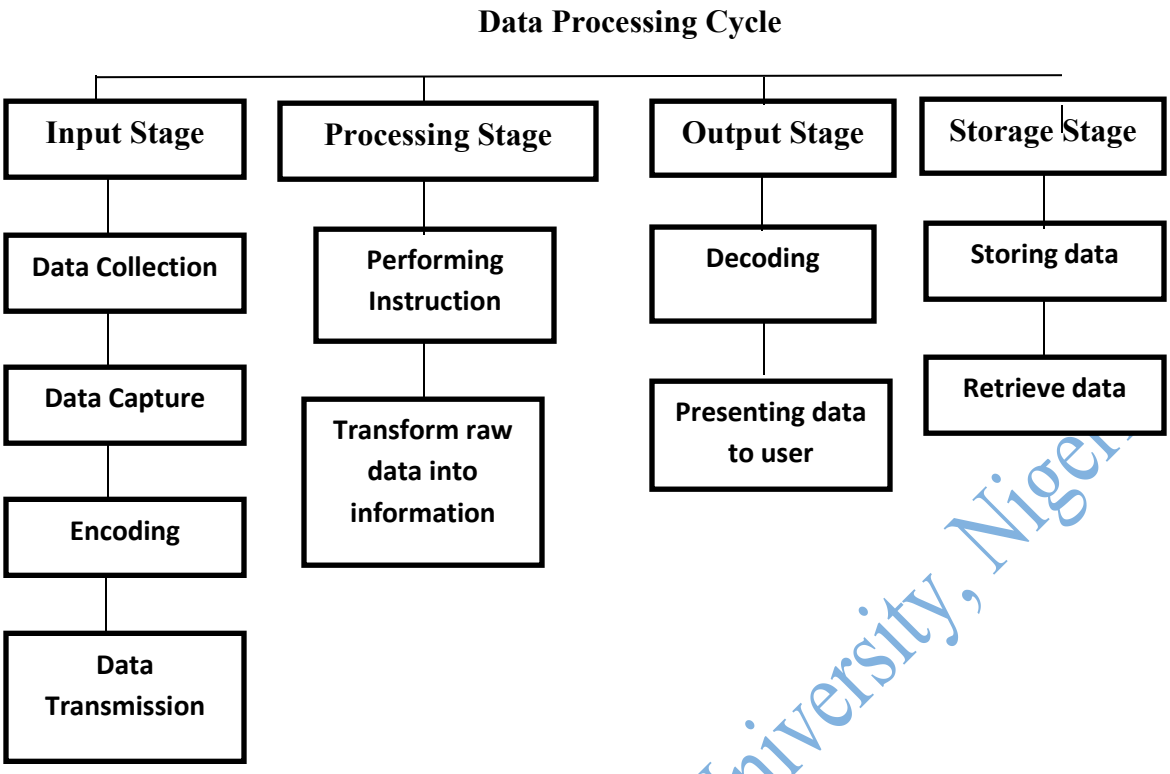


**Figure 2.1: Data Processing Cycle**

**Source: Researcher' Data Processing Cycle, 2023**

The relevance of this theory to the study is its ability to give detailed (step by step) technological change to how data is been processed among health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria which will enhance proper documentation of patients and accurate information retrieval without wasting time. This will also improve patients' health status, health facilities' accessibility and boost medical practitioners' attention to patients.



## 2.3 Review of Empirical Studies

### 2.3.1 Data Processing Practices and Service Delivery

This article demonstrates the caveats of using user surveys to evaluate data quality. Information is difficult to make a direct comparison between the data and the user's experience because information is compiled and incorporated from so many different sources. Data is only made

available to users through analysis and reporting tools. Therefore, the quality of the data that originates in the source systems should not be confused with the quality of the results and how queries are handled. Health data warehouse evaluation could provide additional testing, such as comparing results with current hospital records, while developers responsible for legacy systems should verify data accuracy through automated data auditing[93].

Big Data in Health Care: Applications and Challenges11 discusses how a scholar built a hybrid model called case-based reasoning and fuzzy decision tree (CBFDT) for medical data classification in the areas of breast cancer detection and liver problem diagnosis. In this research, we present a case-based fuzzy decision tree (FDT) model for medical categorization issues, along with its associated methodology and algorithm. From the medical database of the University of California, Irvine (UCI), two sets are chosen to represent liver diseases and Breast Cancer Wisconsin, respectively. This study makes use of more than 900 data sets. Parameter-free, decision-tree induction produces a plausible tree by iteratively picking attributes to branch the tree. This study employs an FDT to generate decision criteria in illness classification by merging diverse medical aspects of liver problems with the Breast Cancer Wisconsin database. Using a data clustering technique, a fuzzy decision tree (FDT), and genetic algorithms (GAs), this classification model builds a medical classification system from scratch. Step one is to choose relevant cases from the UCI data set for further analysis; step two is to partition the case library into smaller clusters; step three is to create the FDT; and step four is to output the classification results[94].

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[95].

A scholar used clustering to achieve patient segmentation from a quantitative perspective. The bulk of the research's information comes from the Irish Hip Fracture Database (IHFD). All the details of a patient's stay, from admission to departure, are recorded there. Data abnormalities are addressed, and new features that may be indications of care quality are extracted, both during the data pre-processing phase. The k-means algorithm is employed here as the partitioned clustering method. To organize data points into groups with shared features, k-means clustering employs a straightforward iterative method. Cluster-based outlier detection and distance-based outlier detection are two of the proposed algorithms for spotting anomalies in large datasets. The algorithms' primary goal was to eliminate anomalies that contribute little to the overall study of health care data. The cluster-based outlier detection method outperforms the distance-based outlier detection method, as measured by F-score and likelihood ratio in an experimental evaluation[97].

A novel clustering approach for multidimensional physical health data based on artificial ant colony optimization was proposed[98]. This method is determined through testing to be an effective and efficient approach to clustering health and medical data for further analysis. A scholar proposed to use the background knowledge of medical domain in the clustering process to predict the likelihood of diseases[99]. The developed algorithm can handle both continuous and discrete data and perform clustering based on anticipated likelihood attributes with core attributes of disease in data point. In this paper, its effectiveness has been demonstrated by testing it on a real-world patient data set.

A researcher carried out an experiment in which 188 participants, 59.0% of whom were female, filled out a number of psychological measures and had assessments for ischemia, pressure, and

thermal pain. Then, independent pain measurements were acquired by using three different experimental modalities of pain, each of which had a number of factors subjected to testing. There were substantial connections discovered between psychological measures and index scores, and cluster analysis of PSI scores revealed that there were four separate clusters[100]. These findings underscore the necessity for further work to discover patterns of responses across multiple pain modalities in order to more properly characterize individual differences in reactions to experimental pain.

An investigation was carried out to examine whether or not data elements that were gathered by machines might perform just as well as a conventional, comprehensive risk-adjustment model that also takes into account data pieces that were evaluated and recorded by physicians [101]. For the purpose of this study, all of the data collected by The National Surgical Quality Improvement Program (NSQIP) between January 1, 2005 and December 31, 2010 were used. Each patient is followed for a period of thirty days after surgery as part of this nationally validated program, during which time more than one hundred thirty-five different variables are measured on that patient. The primary analysis consisted of looking at all of the patients in the database who fit the criteria of having an adverse event and having an operation that was performed by either a general surgeon or a surgeon who specializes in one of the subspecialties of surgery. In the hospital context or within the first 30 days after surgery, multivariate logistic regression models were developed in order to predict either mortality or any complications that may have occurred. After that, the researchers evaluated the ROC AUC of each regression that used objective preoperative risk variables to its matching regression that included all variables. There were a total of 745,053 patients that participated in the study. When comparing models with all variables to models with objective variables, the difference in AUC ranged from 0.0073 to 0.1944 for mortality and from 0.0198 to 0.0687 for complications. According to these findings, it

may be possible to design a risk-adjustment system that has a high discriminating value despite simply using objective variables as inputs. We can lessen worries about reliability and validity, as well as threats of gaming the system by seeking to boost the risk score of patients through subjective characteristics, if we limit the data collection to objective data only. An investigation that was carried out using a retrospective cohort study. In this study, the authors identified all Veterans Health Administration (VHA) patients treated at twelve facilities from 2003 to 2007 who were free of recent cerebral and cardiovascular (CCV) events. They then predicted risk using the Framingham risk score (FRS), logistic regression, generalized additive modeling, and gradient tree boosting[102].

In order to build a consolidated set of parameters and utilize them to develop Cox regression models for heart–lung transplant survival, a researcher used three separate variable selection approaches on a large and feature-rich data set. This allowed the researcher to generate the data set[103]. The primary purpose of this research was to propose an integrated data mining methodology in the hopes that it will increase the accuracy with which outcomes following combined heart and lung transplantation can be predicted. A protocol for the formal request of data was followed in order to get the data files from United Network for Organ Sharing (UNOS). The entire data set includes a total of 61,391 records and 443 variables to work with. The socio-demographic and health-related aspects of both the donors and the recipients were included in these variables. The data collection also contains factors that are connected to the procedures that were carried out. According to the findings, the integrated data-mining methodology offered utilizing Cox hazard models provided a more accurate prediction of graft survival with a wider range of variables than the standard approaches that are typically utilized in the research.

An algorithm developed by a researcher to find association rules between the features gathered from a database of mammograms and the category to which each mammogram belongs[104]. They

confined the discovery of association rules in such a way that the antecedent of the rules is sformed of a conjunction of features from the mammogram, while the consequent of the rules is always the category to which the mammography belongs. This allowed them to determine which features from the mammogram are most predictive of the mammogram's classification. After the association rules have been identified, they are included into the construction of a categorization system that assigns normal, malignant, or benign status to the mammograms. The anamnesis data in a medical database contain the information that is both the most complete and the most detailed. This information includes the disease name, the prescription, the patient's detail information, and so on. It is feasible to discover the association rules that exist between diseases by using this strategy. As a result of this, a unique framework for data mining was suggested, which clusters the data first, and then follows with association rule mining. In the first stage, the database is clustered with the help of the ant system-based clustering algorithm (ASCA) and the ant k-means (AK) algorithm. After that, the ant colony system (ACS)-based association rule mining method is used to mine the association rule for each cluster. Experimentation using the data sets provided by the National Health Insurance Plan of Taiwan reveals that the suggested method is able to uncover the hidden rules that may occur less frequently but have solid correlations between them.

## 2.3 Conceptual Framework

**Independent Variables**

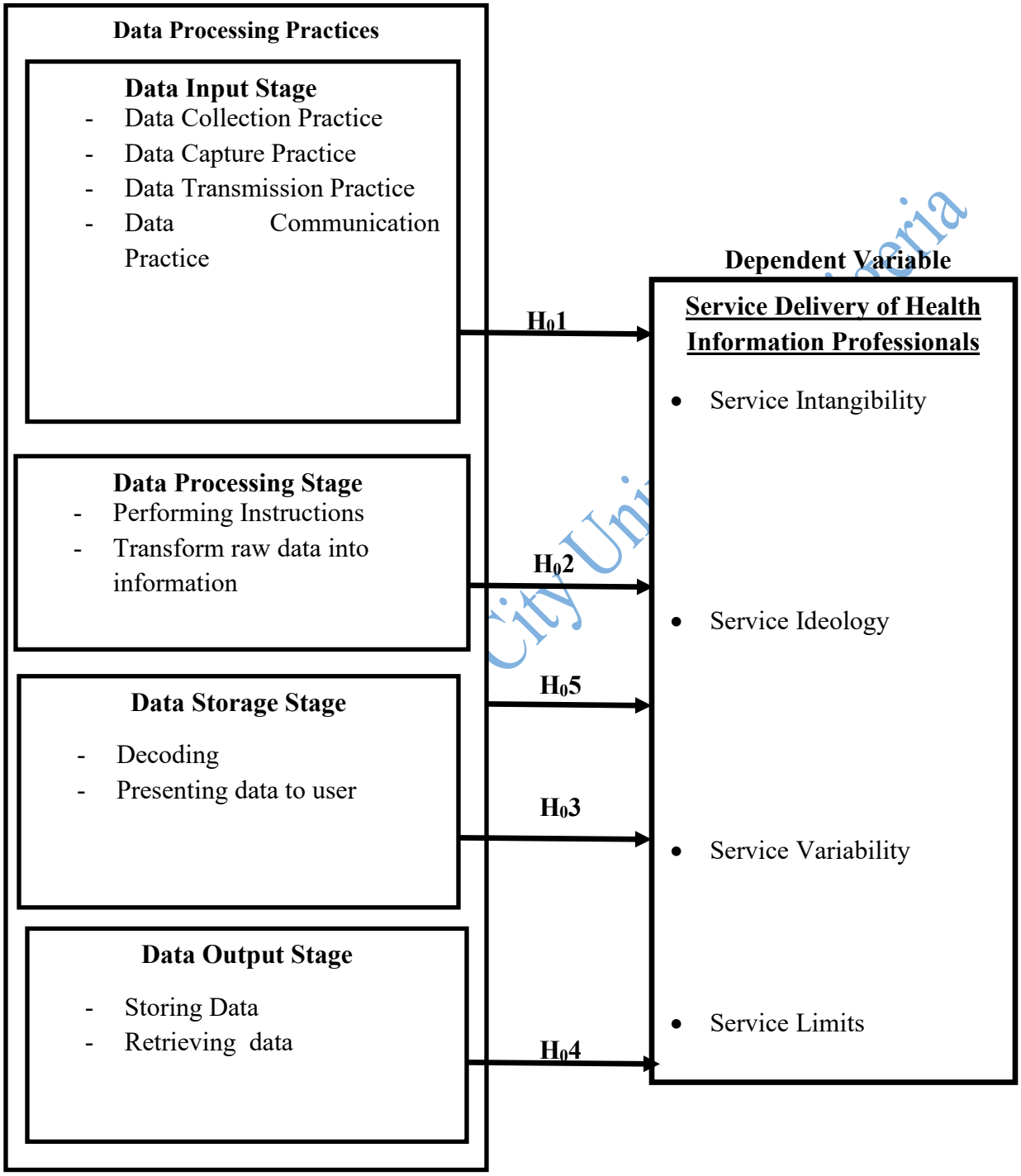


**Figure 2.3: Conceptual Framework**

**Source: Researcher' Conceptual Framework, 2023**

The dependent variable is service delivery of health information personnel, as depicted in the diagram above, and the measures used to assess it are; service intangibility, service ideology, service variability and service limits as adapted from Human Service Delivery Theory[91]. Data Processing Practices is the independent variable and it is measured with Data Input Stage, Data Processing Stage, Data Storage Stage and Data Output Stage as adapted from Data Processing Cycle. As shown in the diagram above, the actions of data input stage were linked to those of service delivery of health information professionals in hypothesis one, the second hypothesis states that data processing stage will be tested on measures of service delivery of health information professionals, hypothesis three will signify the influence of data processing stage on measures of service delivery of health information professionals, hypothesis four will test data output stage on the measures of service delivery of health information professionals. Finally, the fifth hypothesis connects the combined influence of all measures of data processing practices (Data Input Stage, Data Processing Stage, Data Storage Stage and Data Output Stage) to the dependent variable (service delivery of health information professionals).

## 2.5 Summary of Gaps in Literature Reviewed

This chapter has reviewed related literature relevant to this research work. Literature reviewed on the concept of service delivery of health information personnel, explored its meaning and discussed empirical findings on service of health information personnel from series of tertiary hospitals. The review on literature on service of health information personnel showed that data accessibility, data consistency, and data accuracy were strong components of health information personnel service delivery. Literature gives a deep insight into various meanings of health information personnel duty.

Review of literature on service delivery in this study has revealed paucity of studies on service delivery of health information personnel in Nigeria. Literatures reviewed in this study indicate that data processing practices have a strong influence on various components of health information personnel service delivery. Unfortunately, many healthcare center treat health information personnel as ordinary civil servant which has led to decay in our tertiary healthcare sector. Health information personnel are not adequately trained on the professional use of computer skills, professional data processing practices is not guaranteed, they depend on personal efforts for capacity building and further training. Also, literature on reviewed showed that the independent variables (data processing practices) with health information personnel service have been studied individually but most studies on data processing practices and service delivery are based on investigation of mostly other sectors aside healthcare. None of these studies have been specific on health information personnel.

In this world of change, information has become the most dominant resource for the success of organizations. In particular, information is critical if organizations have to meet increasing regulatory and legal requirements. A data management program is mandatory and not a choice to all institutions especially in determining patients' health status. Institutions operating without

a proper data processing systems are likely to experience litigation and health issues, amongst other problems.

This literature addresses the definition of data processing practices and its effective use by health information personnel in tertiary hospitals. An author Marshall McLuhan offered us a useful vehicle to organize the apparent mayhem and confusion surrounding this ever-elusive term. Simply stated, the evolution of the technology has had a direct influence on the easy processing of data. A somewhat cumbersome and relatively manual form of data processing practices forced educators to look at the impact of technology on service delivery of health information personnel especially in tertiary hospitals. Few were done on effect of use of data management on service delivery of employees and none done specifically on health information personnel service delivery. This is the gap the researcher intends to fill as well as explore more on the influence of both data processing practices variable on service delivery by health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria

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## CHAPTER THREE

## Methodology

This chapter describes the research methodology that was employed for the study. Specifically, the chapter outlines research design, population of the study, sample and sampling techniques, instruments for data collection, data collection procedures and methods of data analysis.

### 3.1 Research Design

A cross sectional survey research design was used for the purpose of this study. The purpose of the design is to address the state of affairs as it exists. It was used when collecting information about people's attitudes at work, opinions, habits or any of the variety of education or social issues. The cross sectional survey research design was also used to describe events in relation to Data Processing Practices and Service Delivery of Health Information Personnel in Tertiary Hospitals in Owerri, Imo State, Nigeria.

### 3.2 Population of the Study

The population of the study comprised of all the 121 health information professionals: These are, Federal Medical Centre, Owerri, and Imo State Specialist Hospital, Umuguma Owerri. (Table 3.1).



**Table 3.1: Population of Health Information Professionals (HIP)in Tertiary Health Institutions in Owerri, Imo State, Nigeria.**

| S/n | Name of Health Institutions | Number of HIP |
|---|---|---|
| 1 | Federal Medical Centre, Owerri | 98 |
| 2 | Imo State Specialists Hospital, Umuguma, Owerri | 23 |
| | **TOTAL** | **121** |

**Source: Hospital Records, 2023**

### 3.3 Sample and Sampling Technique

The sample size of this study is one hundred and twenty - one (121) health information professionals. Total enumeration was used because the population is small.

### 3.4 Description of Research Instrument

Data was collected using a structured questionnaire titled: Service Delivery and Data Processing Practices (SDDPP). The instrument is a structured questionnaire adapted from previous empirical studies. This study also adopt the Likert scale design which allowed the researcher provide their opinion about the issue under study.

**Section A**: This section is designed to collect demographic information of respondents and these contains Bio – data of Respondents measured through five factors; Gender, Age, Educational Qualification, Year of Experience.

**Section B**: This section is designed to collect data on Service delivery of health information professionals. The service scale covers measures such as service intangibility, service ideology, service variability and service limits which were adapted from scholar in different context[1,2]. Each of the section for each variable are considered reliable given the reliability tested result reported by scholars. The Cronbach's alpha coefficient for the variables (were 0.7, 0.8. 0.6, and 0.76) respectively. Sample of the items in the questionnaire include: "There is facility put in place for proper storage of patients health records and Service learning experience is directly linked to building health data skills". The response options available to respondents following the Likert-type scale include Very high = 4, High = 3, Low = 2, Very low = 1. The number of items in this section is 9.

**Section C:** This section is designed to collect data on data processing practices. The data processing practices scale which indicates activities that are done. It covers measures such as data input stage, data processing stage, data storage stage and data output stage which were adapted from scholar in different context[3]. Each of the section in the adapted questionnaire is

considered reliable given the reliability tested result reported by scholars. The Cronbach's alpha coefficient for the variables (were 0.7, 0.8. 0.6, and 0.76) respectively. Example of questions is: "Appropriate use of algorithms, formulas, and translation systems and there is provision for uploading and downloading files almost immediately they are needed by the health consultants". The response options available to respondents following the Likert-type scale include Strongly Agree = 4, Agree = 3, Disagree = 2, Strongly Disagree = 1. The number of items in this section is 25.

### 3.5 Validity of Research Instrument

The items for the instrument were gathered through related literature review and adaptation from questionnaires that have been used by other researchers. Both face and content product validity was done with the input of the supervisor and other experts in the field of information management. Corrections made were incorporated in constructing the final questionnaire which was given out to the respondents for the study.

### 3.6 Reliability of the Research Instrument

The researcher subjected the questionnaire to a reliability test to check internal consistency of all items measuring each variable in the study. The reliability of the instrument was done through a pilot study using 30 copies of the questionnaire which was administered to health information professionals in Anambra State University Teaching Hospital which is not part of the study. The result of the reliability test was analyzed using Cronbach Alpha. The result of the reliability test is as follows: Data input – 0.85, Data Processing – 0.75, Data Storage – 0.70, Data Output – 0.80 and Service delivery – 0.75.

### 3.7 Administration and Method of Data Collection

A letter of introduction and project attestation form was obtained from the Department of Information Management, Lead City University which was used to gain permission to conduct the survey from the management of all tertiary hospitals in Owerri, Imo State. A two (2) day training was conducted for five (5) research assistants to ease the administration, retrieval and initial sorting of copies of the questionnaires. The researcher and research assistants worked with the human resource manager of the health institutions to ensure confidentiality of their responses while briefing them on the need for adequacy of responses and advantages embedded in the findings of the study. The copies of questionnaires were given to the institutions according to the proportionate sample for each institution.

### 3.8 Method of Data Analysis

The data that was collected from respondents was analyzed using the descriptive and inferential statistics. Descriptive statistics (frequency distribution, simple percentage and mean) was used to analyze data to answer research question one and two. The justification for using the descriptive analysis is because it helps to analyze all the variables in the study and to provide answers to the research questions raised. Simple regression analysis was used to analyze null hypotheses one to four, while multiple regressions were used for hypothesis five. All hypotheses in the study was tested at 0.05 level of significance. The data collected for the study was analyzed using Statistical Package for Social Sciences (SPSS), Version 28.



**Endnotes**

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**CHAPTER FOUR**

## Results and Discussion of Findings

This chapter establishes the result of the analysis of data collected from the participants in the study and thoughts of outcomes arising from the study.

### 4.1 Data Presentation and Analysis

| Response Rate: | Frequency | Percent |
|---|---|---|
| **Sample Size:** | 121 | 100% |
| **Total Questionnaire Distributed** | 121 | 100% |
| **Total Questionnaire Retrieved** | 118 | 97.5% |
| **Valid Questionnaire** | 118 | 97.4% |

**Source: Field Survey, 2023**

The above data reveals the total number of questionnaire distributed and retrieved. A total number of 121 questionnaire was administered and about 118 was retrieved. The total number retrieved accounts for about 97.5% of the total number of questionnaire administered.

**Demographic Characteristics of Respondents**

The demographic data of the participants were collected and surveyed using descriptive statistics such as frequencies and percentages and presented in tables.



### 4.1.1 Distribution of Respondents by Gender

**Table 4.1: Gender of Respondents**

| Gender | | | | | |
|---|---|---|---|---|---|
| | | Frequency | Percent | Valid Percent | Cumulative Percent |
| | Female | 61 | 51.7 | 51.7 | 51.7 |
| | Male | 57 | 48.3 | 48.3 | 100 |
| | Total | 118 | 100 | 100 | |

**Source: Researcher, 2023**

The above table reveals the gender status of respondents for this study. Considering the fact that the total number of respondents for this study is summed up at 118, the data above has a record of 61 female respondents which account for about 51.7% and 57 male respondents which account for about 48.3%. Going by this, it is concluded that there are more female health information professionals than their male counterpart in teaching hospitals in Imo state, Owerri.

**Table 4.2: Age of Respondents**

| Age | | | | |
|---|---|---|---|---|
| | Frequency | Percent | Valid Percent | Cumulative Percent |
| 20-30 years | 16 | 13.6 | 13.6 | 13.6 |
| 31-40 years | 48 | 40.7 | 40.7 | 54.2 |
| 41-50 years | 31 | 26.3 | 26.3 | 80.5 |
| 51 years and above | 23 | 19.5 | 19.5 | 100 |
| Total | 118 | 100.0 | 100 | |

**Source: Field Survey, 2023**

The above table is showing the age of respondents for this study. With a total number of 118 respondents that serves as the sample size of this study, 48 respondents for this study indicated that they fall within the age range of 31 to 40 years of age. That accounted for about 40.7% of the total number of respondents for this study. 16 respondents affirmed that they are within the age range of 20 to 30 years of age. This accounts for about 13.6% of the total number of respondents. 31 respondents accounted for about 41 to 50 years of age. This is about 26.3% percent. 23 respondents are 51 years of age and above. Going by the above data, it is not out of

place to say that many of the health information professionals in tertiary hospitals in Imo state are very much still in their prime of life and therefore they are very much agile and it is still expected that they can give their best to their workplace.

**Table 4.3: Educational Qualifications of Respondents**

| Educational Qualification | | | | |
|---|---|---|---|---|
| | Frequency | Percent | Valid Percent | Cumulative Percent |
| National Diploma | 19 | 16.1 | 16.1 | 16.1 |
| Higher National Diploma/BSc | 62 | 52.5 | 52.5 | 68.6 |
| MSc | 31 | 26.3 | 26.3 | 94.9 |
| PhD | 6 | 5.1 | 5.1 | 100 |
| Total | 118 | 100 | 100 | |

**Source: Field Survey, 2023**

Above table reveals the educational qualification of the respondents of this study. From the table, 31 of the respondents affirmed that they have a master's degree. 62 claim to have a first degree while 19 claim to have an NAC and Diploma certificate. 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. Adding these two percentages together will actually give us about 78.8% of the total number of respondents for this study. The implication of this is that to a large extent Health Information Professionals in tertiary hospitals in Owerri, Imo State, Nigeria are very much well informed because of their level of education. And if this is the case, the authenticity of this study can be actually relied upon because those that constitute as respondents for those studies are well informed going by their level of education and definitely will give unbiased response to this study. This is not to say that other respondents whose educational qualification fall within the educational category of ND to NAC and Diploma are not well informed, but since those with bachelor's and master's degree

out-number those with lesser qualifications, it is an indication that responses from these category of respondents will be highly reliable.

**Table 4.4: Years of Experience of Respondents**

| Work Experience | | | | | |
|---|---|---|---|---|---|
| | | Frequency | Percent | Valid Percent | Cumulative Percent |
| **Valid** | 1-5 years | 28 | 23.7 | 23.7 | 23.7 |
| | 6-10yrs | 54 | 45.8 | 45.8 | 69.5 |
| | 11-15yrs | 26 | 22.0 | 22.0 | 91.5 |
| | 16yrs and above | 10 | 8.5 | 8.5 | 100.0 |
| | Total | 118 | 100.0 | 100.0 | |

**Source: Field Survey, 2023**

The above table shows the last demographic data for this study. The last demographic table here is about the number of years of experience of the respondents for this study. Form the table above, it can obviously be seen that each of the respondents of this study are well experienced. 26 respondents indicated that they have about 11 to 15 years of work experience. 54 of the respondents say that they are well experienced with having a total number of 6 to 10 years work experience. 10 of the respondents claim that they have about 16 years and above number of years of work experience. Going by these data, it is not out of place to say that health information professionals are very much experienced in their job and are in a very good position to actually give well meaningful detailed account based on what this study will be investigating into. Going by this, it is also safe to conclude that these health information professionals are well experienced in their job.

### 4.2 Presentation of Research Questions

**4.2.1 Research Question One:** What is the Level of Service Delivery of Health Information Personnel in Tertiary Hospitals in Owerri, Imo State, Nigeria

**Table 4.5: 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 effectively. | 40 (33.9%) | 27 (22.9%) | 38 (22.9%) | 13 (11.0%) | 2.8 |
| 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 |
| | 6 | 31 | 62 | 19 | 2.20 |

| | | | | | |
|---|---|---|---|---|---|
| My place of work is very much conducive for the handling of patients' records. | (5.1%) | (26.3%) | (52.5%) | (16.1%) | |
| **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** | | | | | |

**Source: Field Survey, 2023.**

The first research question in this study says "What is the level of Service Delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria? 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. Out of this mean score only the item that says "I feel that patients that use the hospital I am working for always receive up to date information about their health status", attracted a good mean score of 2.80 on a 4 point scale. 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.



### 4.2.2 Research Question Two: Data Processing Practices of Health Information Personnel in Tertiary Hospitals in Owerri, Imo State, Nigeria

**Table 4.6: 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 | 10 | 21 | 48 | 39 | 2.45 |

| | | | | | |
|---|---|---|---|---|---|
| smooth and effective intranet for the transmission of patient data from one unit to another. (Data Transmission Practice). | (8.5%) | (17.8%) | (40.7%) | (33.1%) | |
| 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 | 14 (11.9%) | 23 (19.5%) | 54 (45.8%) | 27 (22.9%) | 2.70 |

| | | | | | |
|---|---|---|---|---|---|
| Instructions). | | | | | |
| 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 Storage Stage** | | | | | |
| I have a clear understanding of decoding patient data in my organization without the assistance of any of my colleagues. (Decoding). | 7 (5.9%) | 20 (16.9%) | 63 (53.4%) | 28 (23.7%) | 1.65 |
| Patient data entry has never been a difficult task for other medical personnel in my organization. (Decoding). | 24 (20.3%) | 25 (21.2%) | 41 (34.7%) | 28 (23.7%) | 1.85 |
| Data presented patients in our organization are always accessed in a way that it is never old-fashioned to our patients. (Presenting data to user). | 13 (11.0%) | 43 (36.4%) | 29 (24.6%) | 33 (28.0%) | 2.65 |
| Electronic platforms used to present data patients in my organization are highly | 37 (31.4%) | 26 (22.0%) | 41 (34.7%) | 14 (11.9%) | 2.75 |

| | | | | | |
|---|---|---|---|---|---|
| accessible and affordable by our patients (Presenting data to user). | | | | | |
| My organization do take into consideration all manner of impaired patients when storing patients data. (Presenting data to user). | 28 (23.7%) | 29 (22.0%) | 33 (28.0%) | 28 (23.7%) | 2.50 |
| **Average Mean: 2.28** | | | | | |
| **Data Output Stage** | | | | | |
| The internet speed in my organization effectively helps me and my colleagues to retrieve patient data effectively. (Storing Data). | 26 (22.0%) | 27 (22.9%) | 42 (35.6%) | 23 (19.5%) | 2.65 |
| My organization uses all manner of formats to store and retrieve patient data in my organization. (Storing Data). | 8 (6.8%) | 36 (30.5%) | 45 (38.1%) | 29 (24.6%) | 2.54 |
| Patients in my place of work have never complained about their data when they access it. (Retrieving Data) | 14 (11.9%) | 25 (21.2%) | 51 (43.2%) | 28 (23.7%) | 2.55 |
| Myself and my colleagues do take into consideration ethical provisions guiding the release of patient data. (Retrieving Data). | 3 (2.5%) | 16 (13.6%) | 67 (56.8%) | 32 (27.1%) | 2.60 |
| Data usage and identification of end-users are always handled effectively and efficiently in my place of work. (Storing data). | 25 (21.2%) | 27 (22.9%) | 40 (33.9%) | 26 (22.0%) | 2.50 |

| | | | | | |
|---|---|---|---|---|---|
| Correction of data imputed wrongly in my place of work are done immediately once the data is accessed and complaints are made. (Storing data). | 7 (5.9%) | 22 (18.6%) | 67 (56.8%) | 22 (18.6%) | 2.45 |

**Average Mean: 2.54**
**Grand Mean: 2.50**

**Research Question Two** of this study is about finding about the prevalent and various data processing types in tertiary hospitals in Owerri, Imo State, Nigeria. 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. The only item that happen to be less performing is that of the item that says "Faculties available in my organization to make the process of transforming patient data into information are highly efficient". 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. A third indicator used in this study to measure data processing practices is that of data storage. This activity attracted a mean score of 2.28 on a 4 point scale. What this implies is that health data is not well stored across tertiary hospitals in Imo state. Some factors may have contributed to this low level deficiency. These factors are seen in the items that make up this indicator. These items are: "I have a clear understanding of decoding patient data in my organization without the assistance of any of my colleagues. (Decoding), Patient data entry has never been a difficult task for other medical personnel in my organization. (Decoding), Data presented patients in our organization are always accessed in a

way that it is never old-fashioned to our patients. (Presenting data to user), Electronic platforms used to present data patients in my organization are highly accessible and affordable by our patients (Presenting data to user) and My organization do take into consideration all manner of impaired patients when storing patients data. (Presenting data to user). Each of this items attracted the following mean scores: 1.65, 1.85, 2.65, 2.75 and 2.50 respectively on a 4 point scale. Out of all these, the first two item seem to have largely contributed to the low level mean score of data storage. The items are: I have a clear understanding of decoding patient data in my organization without the assistance of any of my colleagues. (Decoding), Patient data entry has never been a difficult task for other medical personnel in my organization. (Decoding). The last indicator used in this study to determine data processing practices is data output. The indicator attracted a mean score of 2.54 on a 4 point scale. This means that to an average extent, what data generated from its storage in tertiary hospitals in Imo state quite relevant to patients who patronize the hospitals. Out of all the items that make up this indicator , just a particular one felt below the threshold of 2.50 on a 4 point scale. The item is "corrections of data imputed wrongly in my place of work are done immediately once the data is accessed and complaints are made. (Storing data). This particular item attracted a mean score of 2.45 on a 4 point scale. What this implies is that, data inputted wrongly into the storage platforms of tertiary hospitals in Imo state are not attended to promptly. When this is left unattended to, then it means that, it could have adverse effect on the kind of data generated for patients and medical personnel in the state tertiary hospitals to work on.

**Analysis of Hypotheses**

**$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.**

**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*

**Source: Field Survey, 2023**

This study tested five null hypotheses. The first null hypothesis 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 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.**

**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**

**Source: Researcher , 2023**

The second null hypothesis of this study says "There will be no significant influence of data processing on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria". The result of the null hypothesis has to be rejected because the result revealed that data processing significantly influenced 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.

**$H_0$3: There will be no significant influence of data storage 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 | .425[a] | .181 | .174 | .28340 |

**A. PREDICTORS: (CONSTANT), DATA STORAGE STAGE**

**ANOVA[A]**

| MODEL | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 2.056 | 1 | 2.056 | 25.603 | <.001[b] |
| | Residual | 9.317 | 116 | .080 | | |
| | Total | 11.373 | 117 | | | |

**A. DEPENDENT VARIABLE: SERVICE DELIVERY**
**B. PREDICTORS: (CONSTANT), DATA STORAGE STAGE**

**COEFFICIENTS**

| MODEL | | Unstandardized Coefficients | | Standardized Coefficients | T | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | 1.639 | .127 | | 12.920 | <.001 |
| | Data storage stage | .263 | .052 | .425 | 5.060 | <.001 |

**A. DEPENDENT VARIABLE: SERVICE DELIVERY**

**Source: Field Survey, 2023**

The third null hypothesis of this study says "there will be no significant influence of data storage on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria". The result of the null hypothesis has to be rejected because the result revealed that data storage significantly influenced service delivery. The probability value was at .001, this means that the sub independent variable significantly influenced service delivery. The ***r*** value was .425. This means that with a 42.5% relationship between data storage and service delivery was positive but weak. The adjusted r square has a value of .181. This means that at 18.1% level of variance will data storage affect service delivery, the remaining 81.9% will come from exogenous factors.

**$H_0$4: There will be no significant influence of data output 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 | .046[a] | .002 | -.006 | .31279 |

**A. PREDICTORS: (CONSTANT), DATA OUTPUT STAGE**

**ANOVA[A]**

| MODEL | | Sum of Squares | Df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | .024 | 1 | .024 | .245 | .622[b] |
| | Residual | 11.349 | 116 | .098 | | |
| | Total | 11.373 | 117 | | | |

**A. DEPENDENT VARIABLE: SERVICE DELIVERY**

**B. PREDICTORS: (CONSTANT), DATA OUTPUT STAGE**

**COEFFICIENTS**

| MODEL | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | 2.203 | .134 | | 16.464 | <.001 |
| | Data output stage | .029 | .059 | .046 | .495 | .622 |

**A. DEPENDENT VARIABLE: SERVICE DELIVERY**

**Source: Field Survey, 2023**

The fourth null hypothesis of this study says "There will be no significant influence of data output on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria". The result of the null hypothesis has to be accepted because the result revealed that data output did not significantly influence service delivery. The probability value was at .001, this means that that the sub independent variable did not significantly influence service delivery. The ***r*** value was .046. This means that with a 46% relationship between data output

and service delivery was positive but weak. The adjusted r square has a value of .002. This means that at 2% level of variance will data storage affect service delivery, the remaining 98% will come from exogenous factors.

**$H_0$5: There will be no significant combined influence of the measures of data processing practices (data input, data processing, data storage and data output) 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 | .828[a] | .685 | .674 | .17795 |

**A. PREDICTORS: (CONSTANT), DATA OUTPUT STAGE, DATA INPUT STAGE, DATA PROCESSING STAGE, DATA STORAGE STAGE**

**ANOVA[A]**

| MODEL | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 7.795 | 4 | 1.949 | 61.541 | <.001[b] |
| | Residual | 3.578 | 113 | .032 | | |
| | Total | 11.373 | 117 | | | |

**A. DEPENDENT VARIABLE: SERVICE DELIVERY**
**B. PREDICTORS: (CONSTANT), DATA OUTPUT STAGE, DATA INPUT STAGE, DATA PROCESSING STAGE, DATA STORAGE STAGE**

**COEFFICIENTS**

| MODEL | | Unstandardized Coefficients | | Standardized Coefficients | T | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | .301 | .145 | | 2.080 | .040 |
| | Data input stage | .645 | .064 | .740 | 10.005 | <.001 |
| | Data processing stage | .205 | .040 | .295 | 5.174 | <.001 |
| | Data storage stage | -.019 | .049 | -.030 | -.381 | .704 |
| | Data output stage | .048 | .044 | .077 | 1.100 | .274 |

**A. DEPENDENT VARIABLE: SERVICE DELIVERY**

**Source: Field Survey, 2023**

**The fifth** null hypothesis is from a joint perspective. The hypothesis says "There will be no significant combined influence of the measures of data processing practices (data input, data processing, data storage and data output) on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria. Both data input and data processing only significantly influenced service delivery. The probability level for each of these sub independent variable are as follows: .0041, .00, .704 and .274 respectively. The r value was at .823. This means that the level of relationship between the four sub independent variables and dependent variable is at 82.3%. This means that this percentage is positive but and strong since it is majorly over 50%. The adjusted r square is .685. This means that again from a joint perspective, there is a 68.5% percent contributing factor of all sub independent variables to bring about service delivery. The remaining 31.5% will come from exogenous factors outside all the sub independent variables.

### 4.4 Discussion of Findings

This study is made up of two research questions and five null hypotheses. The first research question says "What is the level of Service Delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria? 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. Studies have actually reported that when service delivery of health workers are low, there is tendency that there will high level deficiency of health care provision in an hospital setting [1]. 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 have access to quality medical records, they will be able to give quality medical care to patients as well [2]. Within the research questions of this study, certain items that make up the each of the research question will also be discussed. For the first research question which says that "What is the level of service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria?, In this research question, the item that says that "Patients' records are positively handled through my data handling ability" attracted a mean score of 1.48 on a scale of 4. The implication of this is that "patient's records are not well handled through the data handling ability of health information professionals. This anomaly also suggests that health information professionals have got to be trained to be able to handle patient's data very well. Another item within the frame of this research question says that "My service learning experience in my place of work so far has directly influenced my record handling skills". This particular item attracted a mean score of 1.91 on a scale of 4. The implication of this is that the training given to health information professionals in Imo state is not yielding much positive result because of the fact what they have learnt so far is not in any way translating to influencing their record handling skills. Probably that is the reason why the item attracted a low mean score. Another item within the service delivery questionnaire that attracted a low mean score says "participation in service learning activities in my place of work helped me to better understand lecture and reading materials". This item attracted a low mean score of 2.02 on a scale of 4. The implication of this item is that even though many health information professionals have been participating in service learning activities in their various place of work to help them better understand lectures and reading materials, this has not yielded any positive result as well. This

also suggests that heads of health information department have got to actually understand how to package effective training for their employees, this will to a large extent contribute to effective service delivery. Another item within the service delivery frame that must have contributed to low service delivery of health information professionals is centered on the item that says "my place of work has state-of-the-art facilities to help health information professionals discharge their duties effectively". Thin particular item attracted a low mean score of 2.30 on a 4 point scale. Invariably, what this means is that there are no state of the art facilities to aid effective service delivery in tertiary hospitals in Imo state among health information professionals. Health information professionals seem to encounter various difficulties during their learning experiences at work. This assertion emanated from the item in the questionnaire under service delivery which attracted a low mean score of 2.20 on a scale of 4. The item says "I never encountered any difficulty all through my service learning experience". The implication of this is that heads of health information departments in tertiary hospitals in Imo state are not sensitive in Cushing the various problems encountered by health information professionals during their learning process. Health information professionals in Imo state in this study have actually admitted certain lapses they encounter professionally when they are inputting patient data in their various place of work. The researcher got to know about this through the mean score of one of the items in this questionnaire under service delivery. The item says "Information about patients in my place of work by myself and colleagues is well written in easy to read language". This item attracted a mean score of 2.15 on a 4 point scale. This implies that errors are always made when inputting patient data into their records and it seems those errors are not corrected on time.

In terms of null hypotheses tested in this study, the first null hypothesis 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 [3, 4, 5, 6].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". The result of this null hypothesis shows that the null hypothesis has to be rejected. This has to be so because the null hypothesis is saying that data processing will definitely bring service delivery. Again studies have shown there to be a strong link between data processing and service delivery [7, 8, 9, 10, 11, 12]. The third hypothesis says that "There will be no significant influence of data storage on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria". The null hypothesis had to be accepted. This is owing to the fact that the probability level in this particular null hypothesis was beyond 0.05 which happens to be the significance level of this study. In this regard the, data storage was seen to not significantly influence service delivery. Studies have actually countered this finding. In research works reviewed in this study, it was found that data storage will actually bring about service delivery [13, 14, 15, 16, 17]. The fourth null hypothesis in this study says that "there will be no significant influence of data output on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria". The findings of this null hypothesis makes the researcher to actually reject this null hypothesis. The reason being that it was found that data output significantly influenced service delivery. Studies have also affirmed this to be true [16, 17, 18, 19]. The last null hypothesis of this study is from a joint perspective. The null hypothesis says "There will be no significant combined influence of the measures of data processing practices (data input, data processing, data storage and data output) on service delivery of health information personnel in tertiary hospitals in Owerri, Imo State, Nigeria". In this particular null hypothesis, only data input and data processing were found to significantly influence service delivery. Other components such as

data storage and data output were found to not significantly influence service delivery. In all, to a large extent, there seems to be high level deficiency with the way and manner health information professionals in Imo state do store health data because this study has revealed that that is one major area there is a big problem.

## Endnotes


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# CHAPTER FIVE

## Conclusion

### 5.1 Summary of Findings

This study has actually been able to investigate the influence of data processing practices on service delivery of health information professionals in tertiary hospitals in Owerri, Imo state. Applying the total enumeration sampling technique, the researcher covered about 118 health information professionals in Owerri, Imo state. The descriptive research survey design was used to systematically analyze data findings in this study. The following were specific findings of this study.

1. Service delivery of health information professionals in tertiary hospitals in Owerri, Imo state is quiet low.
2. 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.
3. Data input practice is seen in this study as the most practiced form of data processing practices among health information professionals in Owerri, Imo state.
4. Among all the indicators of data processing practices, only data storage was found not to significantly influence service delivery of health information professionals in Owerri, Imo state.
5. It was revealed in this study as well that data storage attracted the lowest level of mean score. That implies that, to a large extent health information professionals in Owerri, Imo state are not comfortable with the way and manner they store health records in their various hospitals.
6. Out of all the indicators of data processing, two indicators were found to significantly influence service delivery, these are data input and data processing.

7. Health information professionals in Imo state need adequate, effective training on how to store health data effectively.

### 5.2 Conclusion

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 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.

### 5.3 Recommendations

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 have got to be trained very well for them to know how to use state-of-the-art facilities to store health data effectively.
3. Health information professionals in Imo state have got to be orientated that when health data is wrongly imputed, it must be corrected immediately.
4. Teamwork have also got to be encouraged among health information professionals in Imo state. This will contribute to high level service delivery among health information professionals in the state.
5. Internet facilities across tertiary hospitals in Imo state have got to be improved upon. This will also bring about effective storage and retrieval of health data in hospitals in the state.

### 5.4. Contribution to Knowledge

This study has shown that when health information professionals implement the indicators of data processing, it will definitely bring about high level service delivery. A situation whereby data storage of health data is not effectively and efficiently stored in an hospital, there is every tendency that health care for patients will be at a great peril thereby bringing about severe health issues for such hospital. In a nutshell, what this implies is that, health data storage plays a great role in contributing to service delivery of health information professionals in a state.

### 5.5 Suggestions for Further Studies

The following are suggestions for further studies where this study can improve upon.

1. Available ICT facilities existing in teaching hospitals as it can contribute to effective service delivery of health information professionals in Imo state.
2. Identifying the competence level of health information professionals in health data storage as it correlates with service delivery of health information professionals in Imo state.
3. Physical and behavioral work environment existing in teaching hospitals in Imo state as it correlates with service delivery of health information professionals in Imo state.

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## Appendices

## Questionnaire

## Lead City University, Ibadan

Dear Sir/Madam,

My name is **Nwankwo Christian Chimezurum**. I am a postgraduate student conducting a study titled "**Data Processing Practices and Service Delivery of Health Information Personnel in Tertiary Hospitals in Owerri, Imo State**". I hereby request you to assist me in completing this questionnaire in order to achieve my research objectives. The information provided will be purely for academic purposes and will be treated with utmost confidentiality. Your participation in facilitating the study is highly appreciated.

### Section A: Demographic Data

Please select the correct answer by ticking (√) appropriately in the provided brackets.

1. Gender: (a) Male ( ) (b) Female ( )

2. Age: (a) 20-30 years ( ) (b) 31-40 years ( ) (c) 41-50 years ( ) (d) 51 years and above ( )

4. Educational Qualification: (a) National Diploma ( ) (b) Higher National Diploma/BSc ( ) (c) MSc ( ) (d) PhD. ( )

6. Work experience: (a) 1-5 yrs( ) (b) 6-10yrs ( ) (c) 11-15yrs ( ) (d) 16yrs and above ( )

**SECTION B**:

**Level of Service Delivery of Health Information Personnel in Tertiary Hospitals in Owerri, Imo State, Nigeria**

**Instruction**: The statements in this section concerns service delivery as observed by the health information personnel in tertiary hospitals in Owerri State. Using the four-point Likert scale provided below, please tick the appropriate choice that indicates your opinion on level of service delivery in your institution.

**NOTE**: Strongly Agree (SA) =4, Agree (A) = 3, Disagree (D) = 2, Strongly Disagree (SD) = 1

| S/N | Items | SA 4 | A 3 | D 2 | SD 1 |
|---|---|---|---|---|---|
| **Service Intangibility** | | | | | |
| 1. | My place of work has state-of-the-art facilities to help health information professionals discharge their duties effectively. | | | | |
| 2. | ICT facilities in my place of work available for health information professionals to work with are working efficiently and effectively. | | | | |
| 3. | Patients' electronic health record in my place of work are well secured. | | | | |
| | **Service Ideology** | | | | |
| 4. | Participation in service learning activities in my place of work helped me to better understand lecture and reading materials. | | | | |
| 5. | My service learning experience in my place of work so far has directly influenced my record handling skills. | | | | |
| 6. | I never encountered any difficulty all through my service learning experience. | | | | |
| | **Service Variability** | | | | |
| 7 | Patients' records are positively handled through my data handling ability | | | | |
| 8 | Patients' record issues are positive dealt with in my place of work. | | | | |
| 9 | My place of work is very much conducive for the handling of patients' records. | | | | |
| | **Service Limits** | | | | |
| 10 | Information about patients in my place of work by myself and colleagues is well written in easy to read language. | | | | |
| 11 | My colleagues and me do communicate effectively well with patients in my place of work. | | | | |
| 12 | I feel that patients that use the hospital I am working for always receive up to date information about their health status. | | | | |

**Section C**:

**Data Processing Practices of Health Information Personnel in Tertiary Hospitals in Owerri, Imo State, Nigeria**

**Instruction**: The statements in this section concerns data processing practices as observed in your hospital. Using the four-point Likert Scale provided below, pleases tick the appropriate choice that indicates your opinion.

**NOTE**: Strongly Agree (SA) =4, Agree (A) = 3, Disagree (D) = 2, Strongly Disagree (SD) = 1

| S/N | Items | SA 4 | A 3 | D 2 | SD 1 |
|---|---|---|---|---|---|
| **Data Input Stage** | | | | | |
| 1. | In my place of work, my colleagues and me follow due process in transmitting patient data from one point to another. (Data Transmission Practice) | | | | |
| 2. | My organization has a smooth and effective intranet for the transmission of patient data from one unit to another. (Data Transmission Practice). | | | | |
| 3. | My organization has effective work apparatus for data to be communicated to appropriate units for effective decisions to be taken. (Data Communication Practice) | | | | |
| 4. | The process of patient data communication in my organization do follow international standard of ethical considerations. (Data Communication Practice). | | | | |
| 5. | My organization does not stress or waste patients' time when it comes to capturing their data. (Data Capture Practice). | | | | |
| 6. | I have all the necessary skills to input patients' data effectively. (Data Collection Practice). | | | | |
| 7. | My organization has state-of-the-art facilities when it comes to collection of patient data. (Data Collection Practice). | | | | |
| 8. | In my place of work, I have all the necessary tools input patient data effectively and efficiently. (Data Capture Practice). | | | | |
| **Data Processing Stage** | | | | | |
| 9. | I make sure that I follow laid down rules and regulations in processing patient data in my organization (Performing Instructions). | | | | |
| 10. | Regardless of my own opinion or expertise, I apply industry standard knowledge when processing patient data | | | | |

| | | | | | |
|---|---|---|---|---|---|
| | in my place of work (Performing Instructions). | | | | |
| 11. | 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). | | | | |
| 12. | Faculties available in my organization to make the process of transforming patient data into information are highly efficient. ((Transforming raw data into information). | | | | |
| **Data Storage Stage** | | | | | |
| 13. | I have a clear understanding of decoding patient data in my organization without the assistance of any of my colleagues. (Decoding). | | | | |
| 14. | Patient data entry has never been a difficult task for other medical personnel in my organization. (Decoding). | | | | |
| 15. | Data presented patients in our organization are always accessed in a way that it is never old-fashioned to our patients. (Presenting data to user). | | | | |
| 16. | Electronic platforms used to present data patients in my organization are highly accessible and affordable by our patients (Presenting data to user). | | | | |
| 17. | My organization do take into consideration all manner of impaired patients when storing patients data. (Presenting data to user). | | | | |
| | **Data Output Stage** | | | | |
| 19. | The internet speed in my organization effectively helps me and my colleagues to retrieve patient data effectively. (Storing Data). | | | | |
| 20. | My organization uses all manner of formats to store and retrieve patient data in my organization. (Storing Data). | | | | |
| 21. | Patients in my place of work have never complained about their data when they access it. (Retrieving Data) | | | | |
| 22. | Myself and my colleagues do take into consideration ethical provisions guiding the release of patient data. (Retrieving Data). | | | | |
| 23. | Data usage and identification of end-users are always handled effectively and efficiently in my place of work. (Storing data). | | | | |
| 24.. | Correction of data imputed wrongly in my place of work are done immediately once the data is accessed and complaints are made. (Storing data). | | | | |

## Bio-data

### A. Personal Data

1. Full Name: Christian Chimezurum NWANKWO

   Email: zurumchrii@gmail.com

   Phone: 08037960393

2. Date of Birth: 25th, October, 1980

3. Nationality: Nigerian

4. Next of Kin: Christian Funmilayo Mary

   Address of next of kin: 36b Orlu Road, Amakohia, Owerri, Imo State

### B. Educational Background with Dates

| Institutions Attended | Qualification Obtained | Dates |
|---|---|---|
| Lead City University | BSc. | 2019 |
| Nmadi Azikiwe University Teaching Hospital | HND | 2007 |
| Nmadi Azikiwe University Teaching Hospital | ND | 2005 |
| Abia State College of Health Technology, Aba | NC | 2003 |
| Ikwuorie Comprehensive Secondary School, Ukwa East, Abia State. | SSCE Certificate | 1998 |
| Ikwuorie Comprehensive Secondary School, Ukwa East, Abia State. | Primary school Certificate | 1992 |

### C. Working Experience with Dates

**1** Chief Medical Records Officer (FMC, Owerri, Imo State) 2023-date

2 Assistant Chief Medical Records Officer (Federal Medical Centre, Owerri, Imo State, Nigeria 2020 -2023

3 Principal Medical Records Officer(FMC, Owerri, Imo State) 2017 – 2020

4 Senior Medical Records Officer (FMC, Owerri, Imo State) 2014 – 2017

5 Medical Records Officer (FMC, Owerri, Imo State) 2010 – 2014

**D. Awards and Fellowships** Nill

**E. Membership**

a. Member Health Records and Information Management Association of Nigeria.

b. Examiner, Health Records Officers Registration Board of Nigeria

c. Member National Institute of Office Administration and Information Managers.

**F. Publications**

a. A retrospective study of epidemiology of Neonatal Jaundice 2000-2006 in NAUTH-Nnewi, 2017

b. Knowledge and attitude of health care workers towards health records keeping in FMC, Owerri, LCU, 2019

c. Influence of Leadership style on health care workers performance in FMC, Owerri, 2020

**G. Conferences Attended with Dates**

a. Workshop on International Classification of Diseases (ICD 11th edition) and electronic health records, Abuja-Nigeria, June 2023

b. Training/Workshop on International Classification of Diseases (ICD) Abuja, Nigeria, September, 2022

**H. References**

1. Sophia V. Adeyeye PhD.
   Head of Department, Information Management
   Lead City University, Ibadan, Oyo State, Nigeria
   08061127798
2. Emperuru A. C (MRS)
   Deputy Director, Department of Health Records
   Federal University Teaching Hospital, Owerri, Imo, State
   08033415440

_____ _____

Signature Date

**The University Compliance Certification**

This is to certify that this thesis by Christian Chimezurum NWANKWO with Matriculation No. LCU/PG/002527 in the Department of Information Management, Lead City University, Ibadan, is in full compliance with the approved university format and style.



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**Signature** **Date**

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