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The Impact Of Machine Learning Algorithms On Benchmarking Process In Healthcare Service Delivery

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THE IMPACT OF MACHINE LEARNING ALGORITHMS ON BENCHMARKING PROCESS IN HEALTHCARE SERVICE DELIVERY

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DEDICATION

This work is dedicated to The Almighty God for giving me the grace, knowledge, and wisdom to complete this work.

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Author

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CHAPTER ONE

1.0. Introduction

Currently, organizations have adopted and implemented a variety of innovative management philosophies, approaches, and techniques to stay competitive in an ever-changing global economy [1]. Benchmarking is one of such techniques used by organizations to stay competitive [2]. Benchmarking is a powerful quality tool, contributing to securing best practice and improve performance [3]. It provides an opportunity both internally and externally in an organization, to review and compare practices against agreed performance criteria. The comparisons enable key areas for securing best practice to be identified and action to be taken to achieve it. Thus, it is a means of harnessing and generating energy and creativity. Camp, [4] defined benchmarking as the continuous process of measuring products, services, and practices against the toughest competitors or those companies recognized as industry leaders'.

Several types of benchmarking exist that organizations might choose to implement, depending on the project and/or resources involved. This includes internal, competitive, functional and generic benchmarking. *Internal benchmarking* is a comparison of similar internal operations, functions, and processes within a single organization. *Competitive benchmarking* involves comparing processes, products, and services between two organizations. *Functional benchmarking* involves making a comparison between similar functional activities in different industries. *Generic benchmarking* is best used when an important process needs significant improvement regardless of the industry or organization you compare with. Benchmarking is applicable to the healthcare sector, service delivery, manufacturing, military etc.

This research focuses on benchmarking in the healthcare sector. Ellis, [5]; Amina et al., [6] described benchmarking in the healthcare sector as the process of comparative evaluation and identification of the underlying causes leading to high levels of performance. Performance measurement might seem strange to other organizations, but the concept of measuring and monitoring performance is not new to the healthcare sector. Requirements for the public overview of healthcare facilities demand that performance data be collected, analyzed and monitored for reimbursement, Federal and State record keeping, and accreditation purposes [7]. As a result, most healthcare facilities already track key performance indicators

(KPIs). As Federal and State regulations require the reporting of more data, healthcare facilities will be in an even better position to assess their performance and share comparative information about performance and operations with other facilities for mutual benefit.

1.1. Problem Statement

Indeed, the greatest value to be gained from all the performance data that healthcare facilities are gathering may well emerge from the process of comparing that data. The comparison process has seen healthcare management face challenges in analyzing data as the advent of big data has seen them amass tons of data and is putting unprecedented pressure on health care providers to better manage the cost and quality of care they deliver [8],[9]. This challenges such as low expertise in data analysis and data security [10] has led to;

i. High patient boarding rates

ii. High patient wait-times

iii. High re-admission rates

iv. Low patient satisfaction

v. Poor quality service, and

vi. Increased waste in clinical resources.

An emergency department (ED) is a medical treatment facility or a department responsible for the provision of medical and surgical care of patients who present themselves without prior appointment either by their own means or via an ambulance. According to Chalfin et al., [11]; Higginson, [12] who reported that due to the unplanned nature of patient attendance, the ED is facing overcrowding, heavy emergency resource demand and inefficient performance has become a major barrier to receiving a high quality and timely medical care which compromises patient safety. Patients who visit the ED often face long waiting times or high boarding rates as they are not admitted into the intensive care units (ICUs). High patient boarding rate is the practice of keeping patients in the ED after they have been admitted to the hospital because no inpatient beds are available. This practice often results in several problems, including ambulance refusals, prolonged patient waiting times, and increased suffering for those who wait, lying on stretchers in ED corridors for hours, and even days, which affects their care, comfort and the primary work of the ED staff taking care of ED patients. Studies by Hoot et al., [13] reports that when EDs are inundated, their ability to respond to community emergencies and disasters may also be compromised.

The advent of computing has facilitated in the collection of large volume of heterogeneous data from multiple sources and this is posing challenges for companies [14]. Researchers have developed machine learning algorithms that will help companies analyze their data. Machine learning is an application of artificial intelligence that provides systems the ability to automatically learn and improve from experience. These algorithms will be used for comparative analysis of the data received from companies in areas where low performance is being perceived to bring about improvements.

1.2. Research Objective

The objective of this research is to increase the performance of the emergency department (ED) of a hospital by reducing the patient boarding rates via: the integration of a hybrid machine learning algorithm into a systematic benchmarking process for performance measurement and analysis.

1.3. Justification of the study

The healthcare sector has shown tremendous growth over the years and this research has theoretical and practical value to hospitals, as it aids researchers in developing and validating generally applied frameworks aimed at facilitating the utilization of machine learning algorithms in a structured benchmarking process for data analysis. The findings of this study act as a decision support tool for management of hospitals in their steps to developing a sustainable competitive advantage and commitment to organization's strategy. It also assists policy-makers in developing policies and strategies which would evaluate the impact of performance measurement in improving efficiency in different hospital departments.

1.4. Scope of the study

The internal benchmarking is selected for this project and this limits us to two departments within a selected hospital for comparative analysis (benchmarking). The research was carried out using data collected from the electronic health records [15] of the selected hospital. The independent variables (input) includes the total number of emergency room visits, average daily emergency room visits, the percentage of leaving before screening, the percentage of leaving without being seen, the percentage of revisits etc. While the dependent variables include emergency room turnaround time, inpatient boarding time, the percentage of emergency room patients admitted to hospital etc.

1.5. Limitations of the study

Although the research has reached its aims, there were some unavoidable limitations. First, because of the time limit, this study was conducted only on a small data size collected from EHR. Secondly, the slow computation time spent while running the algorithms.

1.6. Organization of The Report

This report consists of six chapters which will cover the analysis and development of machine learning algorithm that will be used in a structured benchmarking process for analysis. Here is an overview of the content of each chapter presented:

- Chapter One: this chapter introduces the problem, gives an overview of the study and describes the needs of benchmarking in organizations. This chapter also discusses the research objectives, justification, scope and limitation of the study.
- Chapter Two: this chapter covers the literature review which is the previous related work regarding existing definitions of quality, benchmarking, analytical tools used in benchmarking analysis and overview of machine learning algorithms.
- Chapter Three: this chapter explains the details of the methodology which covers data gathering, collection, and analysis which integrates machine learning algorithms into the benchmarking process.
- Chapter Four: this chapter discusses the methodology and tools implemented in a case study.
- Chapter Five: this chapter discusses the results of the analysis.
- Chapter Six: this chapter explains the conclusions, recommendations, and future works to improve this study.

CHAPTER TWO

2.0. Literature Review

2.1. Introduction

This chapter discusses the relevant quality improvement tools that have been developed and utilized by researchers. Moreover, this chapter presents the current techniques used for benchmarking and performance measurement in different sectors with focus on the healthcare sector. It also presents the techniques that would be used in the proposed methodology. In additions, it discusses the previous researches that has been done using these techniques.

2.2. Overview of Quality in Different Sectors

Published studies have emphasized the importance of quality in a product, process and service offered by a company. Quality is an essential means of competing in today's rapidly changing global marketplace [16]. Quality cannot be discussed without giving credit to its founders Joseph M. Juran and W. Edwards Deming [17]. The term quality means different things to different sectors and is defined based on its applicability in these sectors such as manufacturing, automotive, healthcare, agriculture etc.

Quality in the automotive industry has gained the attention of practitioners, researchers and academics since the United States (U.S) car manufacturers lost significant market share to international competition in the 1980s (Devaraj et al., [18]; Garvin, [19]; Zeithaml, [20]; Mitra and Golder, [21]; Aaker, [22]; Stylidis et al., [23]) described quality in the automotive sector as the subjective consumer judgement regarding overall product superiority, relative to alternatives. According to business dictionary, quality in manufacturing is defined as a measure of excellence free from defects, deficiencies and significant variations which is brought about by strict and consistent commitment to certain standards that achieve uniformity of a product to meet customer requirements. Another notable definition of quality is by Drucker [24]; Lee & Fawcett [25] who argued that quality in a product or service is not what the supplier puts in, but it is what the customer gets out and is willing to pay for. Shewfelt [26], described quality as the absence of defects or a degree of excellence in agricultural products.

Unlike the other sectors, quality in healthcare is based on the services delivered by hospitals which are patient-centered. Donabedian, [27] presented healthcare quality as the application of medical science and technology in a manner that maximizes its benefit to health without correspondingly increasing the risk. Øvretveit, [28] suggests quality care as the provision of care that surpasses patient expectations and achieves the highest possible clinical results with the available resources. According to Schuster et al., [29], good healthcare quality involves providing patients with appropriate services in a technically competent manner, with good communication, shared decision making, and cultural sensitivity. Lee et al., [30] argued that quality in healthcare means doing the right things and making continuous improvements, obtaining the best possible clinical outcome, satisfying all patients, retaining talented staff and maintaining sound financial performance. The Institute of Medicine defines quality as the degree to which healthcare services for individuals and population increases the likelihood of desired healthcare outcomes and is consistent with the current professional knowledge. Also, Naidu, [31]; WONCA, [32]; Allen, [33]; Burnett et al., [34] described quality in healthcare as the best possible health outcomes given the available circumstances and resources, centered on patient care. Giannini, [35] described that there are three standard levels of quality in healthcare; the first level is *conformance quality* which is the outcome of the work meets the minimum standard requirement set by an organization. The second level is *requirements quality* in which the supervisor is responsible for meeting the expectations of customers, so it is perceived that he is running a good organization. The third level is *quality of kind*, where the service exceeds customer expectations.

These authors have made notable contributions to quality which is seen as a vital foundation on which customer satisfaction is built. Looking at these definitions, we can conclude that the influence of quality on customer perceptions and consumption behavior has led experts to call quality the most important factor for long-term competitive success [25]. Having seen that quality is what retains customers perception in a company, companies are striving every day to ensure that the quality of their products, processes and services are high in other to meet customer’s requirements. This has led to the implementation of different quality improvement tools and measures in companies as presented below.

2.3. Quality Improvement

Batalden & Davidoff, [36], in their studies, described quality improvement in healthcare as the joint and continuous efforts of healthcare professionals, patients, researchers, payers, planners and educators – to make the changes that will lead to better patient health outcomes, system performance and professional development. Looking at quality from the Institute of Medicine's perspective, an establishment's current system is described as how things are done now, whereas health care performance is defined by an organization's efficiency and outcome of care, and level of patient satisfaction. Quality is directly linked to an organization's service delivery approach or underlying systems of care. To achieve a different level of performance and improve quality, an organization's current system needs to change. A variety of quality improvement models exist to help organizations in collecting and analyzing data as well as test changes. Some of the improvement models, approaches and tools include lean operations, six-sigma, business process re-engineering, experience-based co-design, model for improvement, statistical process control, theory of constraints, total quality management (TQM), value methodology and benchmarking to improve their processes, products, and services to stay competitive.

2.3.1. *Lean Operations*

Lean is a set of operating philosophies and methods that help create a maximum value for patients by reducing waste in resources such as time, money, supplies, goodwill etc. [37]. When lean thinking is applied rigorously throughout an entire organization, lean principles can have a positive impact on productivity, cost, quality and timely delivery of services to ensure customer's needs are met. See figure 1 for tools used in lean operations.

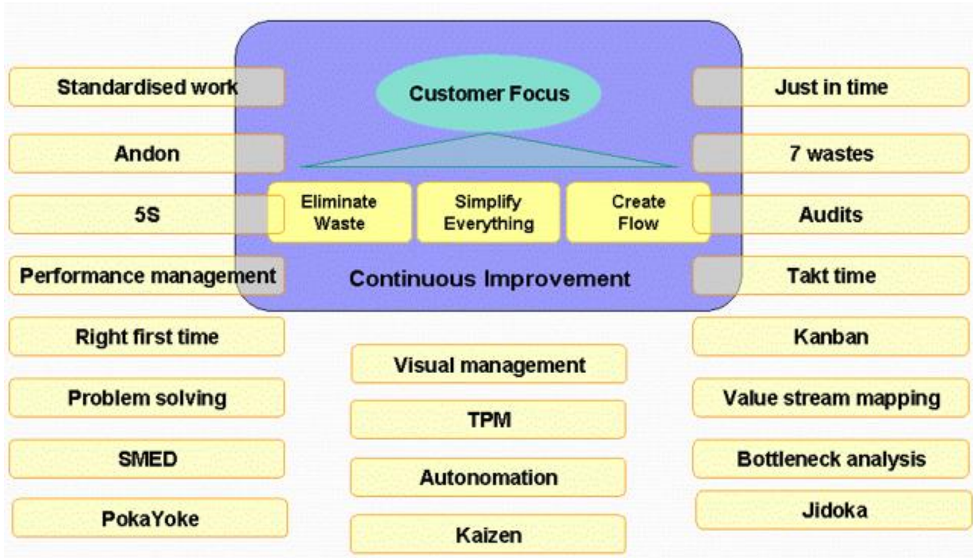

Figure 1: Lean Manufacturing Tools (Source: Earley, [38])

2.3.2. *Six Sigma*

This methodology aims at predominantly making processes more uniform and precise through the application of statistical methods [39]. According to the American Society of Quality, Six Sigma is a method that provides organizations tools to improve the capability of their business processes. A rise in performance and reduction in process variation culminates in a reduction of defect and improvement in employee morale, profits, quality of products or services as well as increased customer satisfaction. Six Sigma is a quality term generally used to indicate a process is well controlled within process limits of $\pm$ 3s from the center line in a control chart and requirements or tolerance limits from $\pm$ 6s from the center line. See figure 2 for tools used in Six Sigma.

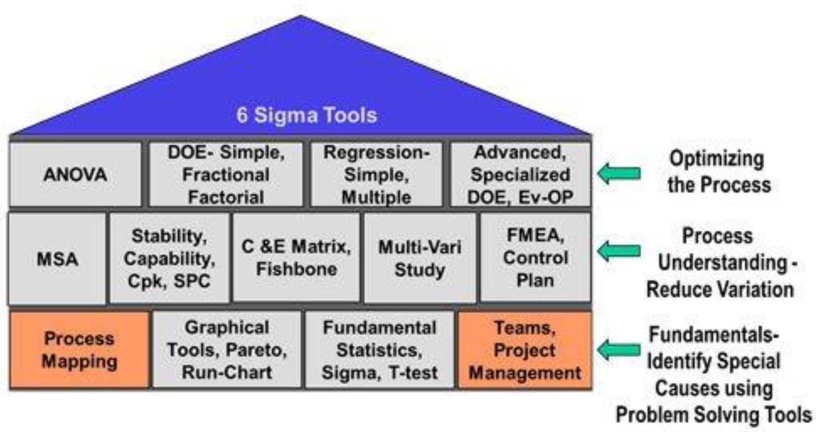

Figure 2: Some of the tools used in Six Sigma (Source: http://www.manufacturingsuccess.org)

2.3.3. *Business Process Engineering*

This approach involves the act of recreating a core business process with the goal of improving customer service, product output, quality and reducing operational cost [40]. Organizations are restructured around key processes rather than specialist functions. By moving away from traditional methods in this way, organizations can identify waste and become more streamlined. Steps followed to ensure successful BPR in an organization is shown in figure 3.

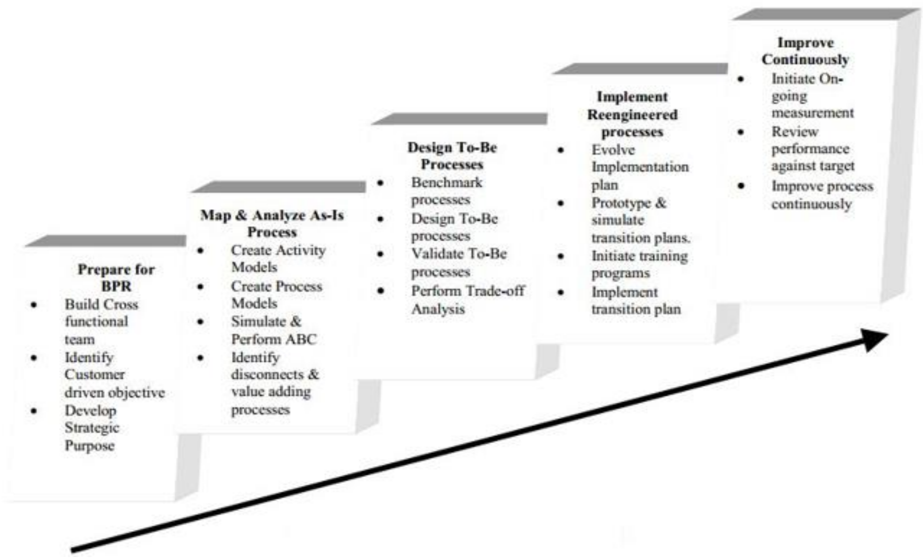

Figure 3: Business Process Re-Engineering Steps (Source: Bliemel & Hassanein, [41])

2.3.4. *Experience-Based Co-Design*

Experience-Based Co-Design (EBCD) is a tool enables healthcare providers, practitioners, patients, families and other service users to co-design improvement initiatives together in partnership. EBCD allows participants to share their experiences of care through in-depth one on one interviews, observations of group discussions, identifying key points, and assigning negative or positive feelings ([42],[43],[44],[45]). This method of data collection helps to inform health service development and improvement.

2.3.5. *Model for Improvement*

The Model for Improvement (MFI) is a simple and powerful tool in the realization of rapid and significant improvement in care delivery and outcomes. MFI was developed by the Institute for Healthcare Improvement and published in *The Improvement Guide: A Practical Approach to Enhancing Organizational Performance (1996).* The MFI uses the Plan, Do, Study and Act (PDSA) cycle to test the effects of small changes, make them and spread the changes through the organization. Figure 4 depicts the process followed to achieve quality improvement in an organization using MFI.

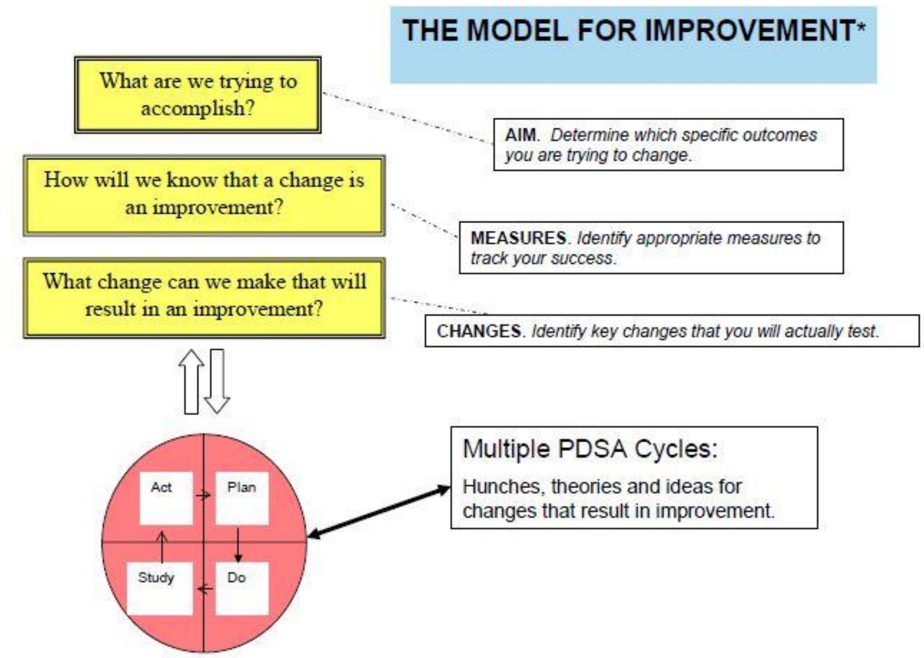

Figure 4: The Model for Improvement (Source: Langley et al., [46])

The MFI begins by asking the following questions:

i. What are we trying to accomplish?

ii. How will we know that a change is an improvement?

iii. What changes can we make that will result in improvement?

With these questions asked, quality improvement teams then proceed to introduce, and test changes designed to achieve the improvement aims using successive PDSA cycles until they arrive on a change they believe will produce the desired results and is ready for implementation.

2.3.6. *Statistical Process Control*

Statistical Process Control (SPC), is an industry-standard method of quality control for measuring, monitoring, controlling and, ideally, improving a process through statistical analysis during the manufacturing process [47],[48]. This helps ensure the process operates efficiently, producing more specification-conforming product with less waste (rework/scrap). SPC can be applied to any process where the conforming product output can be measured. In the mid-1920s, Dr. Walter A. Shewhart developed the fundamentals of SPC and the associated tool of the Control Chart. Key SPC tools include run and control charts, a focus on continuous improvement, and design of experiments. With real-time SPC data, the following can be achieved in an organization;

i. Reduce variability and scrap
ii. Scientifically improve productivity
iii. Reduce costs
iv. Uncover hidden process personalities
v. Instantly react to process changes
vi. Make real-time decisions on the shop floor

2.3.7. *Theory of Constraints*

Theory of Constraints (TOC) was developed by Eli Goldratt in the mid-1980s to help organizations improve their products and services in shorter throughput time and quick inventory turnover. The main goal of TOC is to focus on system improvement. Nave, [49] in his studies presented a system as a series of interdependent processes. An analogy for a system is the chain: a group of interdependent links working together towards achieving a goal. The constraint is a weak link. The performance of the entire chain is limited by the strength of the weakest link. The general process followed to improve the weakest link using TOC is outlined below and in figure 5;

- Identify the system’s constraints
- Exploit the system’s constraints
- Subordinate other processes to the constraint based on decisions from the previous point
- Elevate the system’s constraints
- Repeat the cycle if any constraint is broken

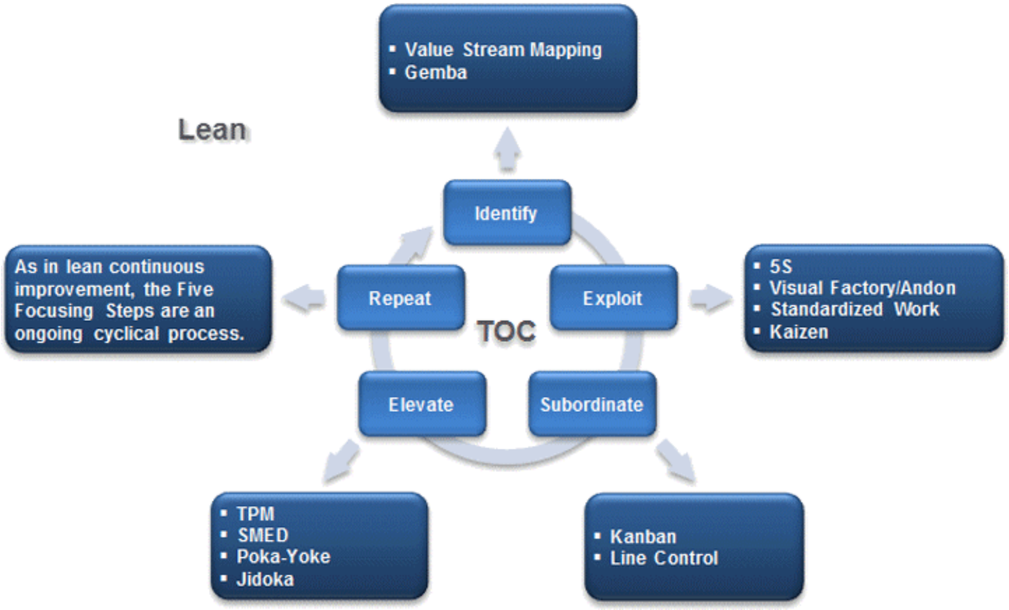

Figure 5: The Five Focusing Steps of Theory of Constraints Process (Source: https://www.leanproduction.com)

2.3.8. *Total Quality Management (TQM)*

This is a term used to describe a management approach to quality improvement. Since then, TQM has taken on many meanings and definitions. TQM cannot be further talked about without giving credit to Dr. W.E. Deming, Dr. J.M. Juran, and others who are the pioneers of quality management. The American Society for Quality defines TQM as a management approach to long-term success via customer satisfaction. [50-52] defined TQM as a management philosophy and a way of thinking that has helped many organizations towards achieving world-class status. These organizations via their processes to produce quality products, and services that meet and exceed the needs of their customers. It creates a culture of trust (amongst employees and customers), participation, teamwork, quality-mindedness, continuous learning and a working culture that contributes towards an organizations success and existence. Below are some of the underlying principles governing TQM;

- Customer-focused
- Total employee involvement
- Process-centered
- Integrated system

- Strategic and systematic approach
- Continual improvement
- Fact-based decision making
- Communications

2.3.9. *Value Methodology*

Value methodology (VM) is a systematic and structured approach to improve the value of products, processes, and services by using an examination of functions [53]. Value is defined as the ratio of function to cost. SAVE International, defines VM as a process that can optimize projects, processes, and product development in significant ways in which through this process, companies, and government agencies regularly decrease costs, increase profits, improve quality and performance, and enhance customer satisfaction. VM is also known as value engineering (VE), value analysis (VA) or value management. It uses a structured 6 step job plan which consists of the information phase, function analysis phase, creative phase, evaluation phase, development and presentation phase (see figure 6).

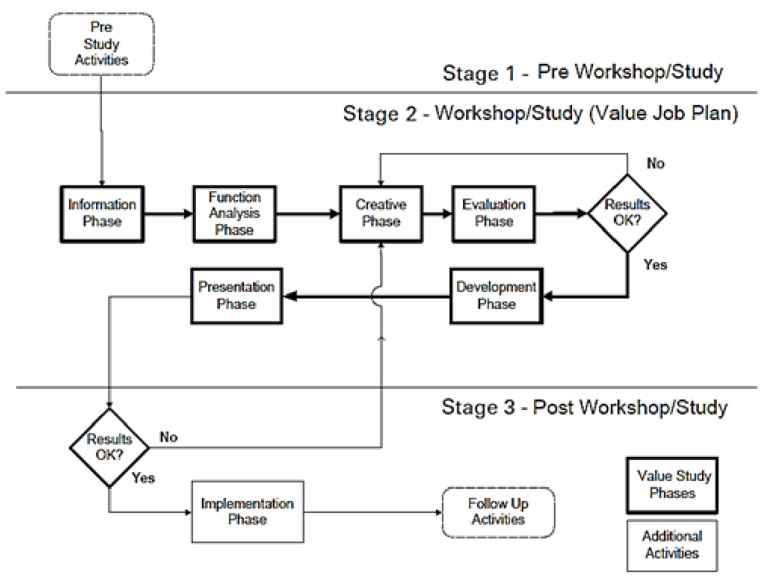

Figure 6: Six Phase Job Plan as Approved by SAVE International (Source: www.value-eng.org)

2.3.10. *Benchmarking*

A lot of definitions on benchmarking exist in literature today. Key themes of this definition include comparison, performance measurement, best practice identification, implementation and improvement

[54]. Benchmarking as defined by [4] as the continuous process of measuring products, services, and practices against the toughest competitors or those companies recognized as industry leaders'. Spendolini, [55] found 49 definitions for benchmarking which he reported in his benchmarking book. Maire et al., [56] proposed that the multiple definitions which have been given express various stages in the evolution of benchmarking and the authors concluded that benchmarking passed four important stages of evolution. During the evolution, some notable definitions were given by ([57],[58],[59],[60],[61],[62],[63],[64]) and a list of others.

According to Anand & Kodali, [54] one of the latest definitions of benchmarking is given by Kumar et al., [65] defined benchmarking as the process of identifying, understanding, adapting to best practices from companies anywhere in the world to help them improve performance. It is an activity that looks inward and outward to find best practices and high performance and then measures actual business operations against those goals.

2.4. Benchmarking: An Evolving Concept

While benchmarking has become commonplace it nevertheless remains a relatively recent phenomenon. The history of benchmarking is well documented ([4],[66],[67],[68],[69],[70]). The Japanese are generally given credit for inventing the concept through their practice of sending managers to visit a wide range of organizations to understand and learn from good business practices. Taichi Ohno, visited the US in 1956 to study has manufacturing was done and used his findings to better develop the manufacturing process in Japan.

Beyond the Japanese, another company involved with developing and promoting the modern conception of benchmarking is Xerox [71]. The story of how Xerox succeeded in closing the performance gap between it and Japanese competitors (Canon) has become part of common benchmarking stories. Xerox began its journey of benchmarking when it sent a team to learn from its Japanese joint-venture partner, Fuji-Xerox. By learning good practices, Xerox was able to secure significant improvements in the quality, costs and time to market of its products. In fact, Xerox's systematic approach to learning and codification of practice from its affiliates led to the popularity of the term benchmarking [58].

2.5. What to Benchmark

Most of the benchmarking literature in the past has focused more on how to develop a benchmarking project once the product, process or service of study has been identified and defined. Various researchers have been able to present studies on how to determine what to benchmark. Partovi, [72] in his studies, presented the use of analytic hierarchy process (AHP) as a means of prioritizing benchmarking projects. Buyukozkan and Maire, [73] propose the use of common factor analysis and principal component analysis as prioritization tools. These tools are not simple to use and require a lot of mathematical and computation analysis in which most data analyst and managers do not have prior knowledge of.

Adam and VandeWater, [74] presented several questions that should be used in investigating and aiding decision making on what to benchmark these questions include:

a. What are the factors for our organization's success?
b. Which products/processes are causing issues?
c. Which processes contributes more to customer satisfaction and which is underperforming?
d. What are the competitive pressures impacting the company?
e. Which processes/functions have the greatest potential for differentiating our organizations from competitors?

Another notable research on what to benchmark is described by [63]. The authors described steps which organizations should follow to determine what to benchmark (see figure 7).

<u>Step 1: Initialize Product and Market Analysis</u>

Information related to product characteristics, target customers, and market competitive priorities should be gathered. This will help to understand what dimensions and activities are most crucial to competitiveness.

Step 2: Critical Dimensions

Information related to customer expectations, perceived quality of different products, the performance of competitors in attending to customer expectations should be gathered. This helps to identify dimensions that need improvement.

Step 3: Critical Processes

All activities and processes belonging to the value stream should be mapped and understand their relationship with the dimensions most in need of improvement. This will focus attention on the activities and processes that impact performance.

Step 4: Performance Measurement

Carry out a qualitative and quantitative assessment of the performance of the critical process or activities. This information will help reveal areas and dimensions in need of improvement.

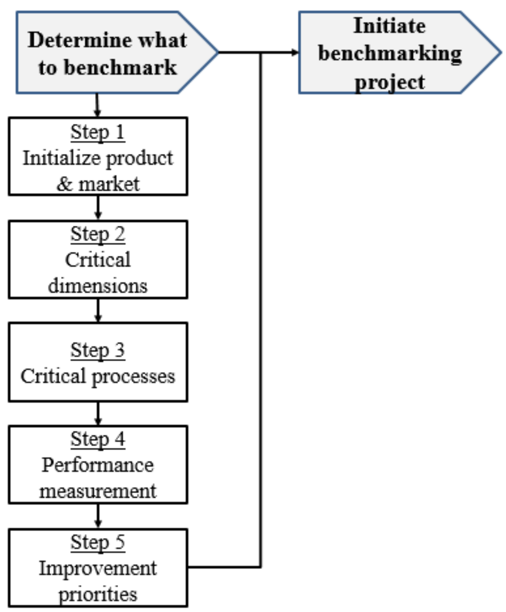

Figure 7: Steps for Defining What to Benchmark (Source: Carpinetti & de Melo, [63])

Step 5: Improvement Priorities

After performing the analysis in the above steps, the dimensions and activities most in need of improvement become evident. With this, the benchmarking project can begin.

If these questions and steps given above are answered and followed properly, by the managers or benchmarking team in the company then, subsequent stages of the benchmarking project will be successful. But if the company fails to answer these questions in the first stage and the appropriate activities of a firm are not prioritized, then subsequent stages of collecting and analyzing benchmarking information may prove futile.

2.6. Varieties of Benchmarking

There are different types of benchmarking as propounded by [75] which includes Internal, Competitor, Industry, Generic, Global, Process, Functional, Performance, Strategic, Competitive and Collaborative benchmarking. This study focuses on the four major types of benchmarking which are internal, external, functional, and generic.

2.6.1. Internal Benchmarking

It is the comparison and measurement of a business process, activity and function to a similar process within an organization to acquire the best internal business practices. This type of benchmarking can be said to be a process of sharing opinions between two departments in the same organization. It typically focuses on reducing variability in performance among departments of the same parent company [76]. The merits and demerits of internal benchmarking are given in Table 1.

Table 1: *Merits and Demerits of Internal Benchmarking*

S/N	Merits	Demerits
1	It is cost efficient	It fosters mediocrity
2	Relatively fast and easy	Limits options for growth
3	A great starting point for future benchmarking	Low-performance improvement
4	Good practice with benchmarking process	It can create an atmosphere of competitiveness
5	Easy access to data	Internal bias
6	Easy to transfer lessons learned	May not yield best-in-class comparisons

2.6.2. External Benchmarking

This type of benchmarking is a direct competitor-to-competitor comparison of a product, process, systems, or services. It provides an opportunity to know yourself and your competition better. Some merits and demerits of external benchmarking are given in Table 2.

S/N	Merits	Demerits
	***Table 2:** Merits and Demerits of External Benchmarking*	
1	Allows you to compare similar processes	Too many legal issues involved
2	A better understanding of your competitor's	Relatively low-performance improvements
3	Allows for possible partnership	It is limited by trade secrets
4	It is useful for planning & setting goals	Sometimes, misleading information may be provided
5	Helps to search for best practices	Competitors could capitalize on your weaknesses

2.6.3. Functional Benchmarking

Functional Benchmarking is described as a comparison to similar or alike practices within the same department of an organization or similar functions outside the immediate organization [77]. It might identify practices that are superior in your functional areas in whatever company they may exist. A typical example of this type of benchmarking is comparing the IRS collections process against those of Discover Credit Card Company. Table 3 gives merits and demerits of functional benchmarking.

***Table 3:** Merits and Demerits of Functional Benchmarking*

S/N	Merits	Demerits
1	It provides industry trend information	Diverse corporate culture
2	Quantitative comparisons	Must be able to visualize how to adapt the best practices
3	It leads to better improvement rates	Common functions can be difficult to find
4		Takes more time than internal benchmarking

2.6.4. Generic Benchmarking

Camp, [4] states that generic benchmarking is a pure form of benchmarking. It theorizes dissimilar business processes or functions that can be practiced in the same way regardless of the organization. The focus is on being innovative and gaining insight into excellent work processes rather than on the business practices of a specific company or industry. A typical example of this type of benchmarking is when a Veterans Administration hospital's check-in process is compared to a hotel's check-in process. The merits and demerits of generic benchmarking are given in table 4.

***Table 4:** Merits and Demerits of Generic Benchmarking*

S/N	Merits	Demerits
1	A high payoff when implemented properly	It is a difficult concept
2	Non-competitive/threatening	Difficult to identify best-in-class
3	It is innovative	Lon planning time
4	High potential for discovery	Highly reputable companies are inundated with requests
5	Examines multiple companies	High risk associated with this type of benchmarking

2.7. Benchmarking Process / Models

Over the years, scholars have developed and presented different theoretical and practical benchmarking models that suit the academic, consulting, and organization projects. Some of these models and approaches have evolved from the original 10 (ten) step, 4 (four) phase model developed by Xerox in 1996 [78]. Watson, [70] reported 69 different benchmarking models in his work. Zairi and Leonard, [79] benchmarked 14 different models. Kozak and Nield, [80] identified 40 different models which he explained that majority of the models originates from academia while the rest from organizations. Anand and Kodali, [54] benchmarked 35 different frameworks against each other in search of a good framework. Many organizations such as Post Office, American Express, Xerox, McKinsey & Company, BBC, Rover Group, Texas Instrument and IBM [81] all have their own guides and benchmarking methodologies.

Jetmarova, [78] conducted studies to identify the best model for benchmarking comparing all the existing models. The author reported that each model differs from one another in the number of steps and phases, however, the basics are similar because it included; identifying benchmarking subjects, data collection, determining current gap, projecting future performance, communication findings, establishing goals, developing an action plan, and implementation. The author developed a benchmarking model based on the existing models which can be adapted and modify for any enterprise project and is seen in Figure 8 and explained in Table 5.

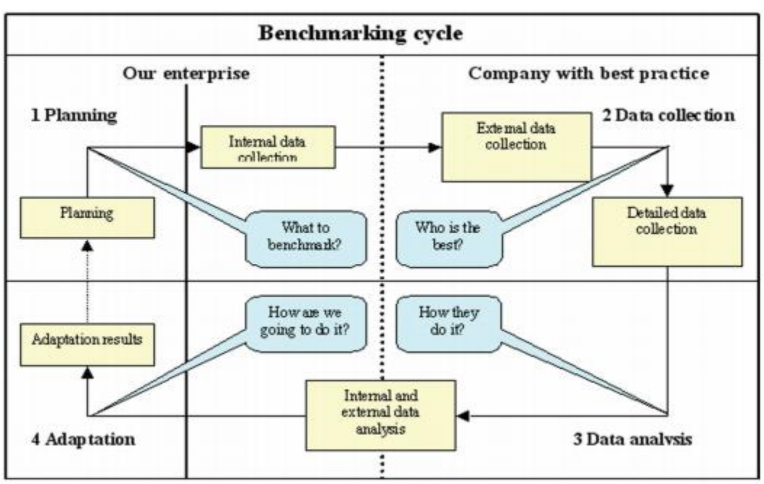

Figure 8: Best Practice Benchmarking Cycle (Source: Jetmarova, [78])

Table 5: Benchmarking phases and steps (Source: Jetmarova, [78])	
Phases	**Steps**
Planning	Defining the benchmarking & objectives
Data Collection	Internal & external data collection, finding a benchmark partner, gathering and aggregating data
Analysis	Converting data to information, sorting, organizing & monitoring, removal of errors, detecting performance differences, identifying processes which can be improved, formulating new goals
Adaptation	Plan creation, implementation of best practices

From the conducted literature review, it is observed that a lot of studies were theoretical, and few were based on practical applications of benchmarking. Authors who presented benchmarking in a practical format utilized different methods for benchmarking analysis. Table 6 presents a seminal study showing the existing notable research work.

Table 6: *Seminal Studies Timeline*

Author: Journal	Year	Method / Findings
e Silva & Camanho, [82]; *Data Analytics Application in Education*	2017	Demonstrates the use of data analytics to examine the performance of secondary schools based on their ability to promote student achievement during higher education.
Kwon, et al. [83]; *Elsevier*	2017	Proposed a three-stage performance modeling using data envelopment analysis (DEA) and neural network (NN) for better practice benchmarking.
Bereskie, et al. [84]; *Environmental Monitoring and Assessment*	2017	The authors proposed a hierarchical risk-based water quality performance benchmarking framework. The framework incorporates fuzzy-rule based modeling which is used to address imprecision associated with measuring performance based on water quality.
Rautu, et al. [85]; *ScienceDirect*	2017	Utilized data analysis charts for benchmarking the operation of drinking water supply systems against a recommended standard given by the International Water Association.
Ozcan, [86]; *International Series in Operations Research & Management Science*	2014	Discussed on the use of DEA for performance assessment of hospital technical efficiency.
Dai & Kuosmanen, [87]; *Omega*	2013	Proposed an approach to benchmarking that combines frontier estimation techniques with clustering methods. Clustering is used to identify groups of decision making units and frontier estimation technique is used for performance measurement.
Nikjoo, et al., [88]; *Journal of Community Health Research*	2013	Utilized AHP in the identification of key performance indicators (KPIs) required for benchmarking as the authors emphasized that the right KPIs is needed for successful benchmarking in the healthcare sector.
Amerinet, [89]	2011	Utilized data analysis charts for collaborative benchmarking to increase efficiency and reduce cost in a surgical suite.
Buyukozkan et al., [90]; *Expert Systems with Applications*	2011	Developed a decision-making fuzzy AHP model to evaluate perceived service quality in the healthcare sector; The results showed that hospitals should focus on empathy,

		professionalism, and reliability to provide satisfactory service.
Salem, [91]; *International Journal of Trade, Economics & Finance*	2010	Proposed a model of using analytic hierarchy process (AHP) to determine the best criteria needed for benchmarking.
Farsi et al., [92]; *Annals of Public & Cooperative Economics*	2006	Explored stochastic frontier analysis on several panel data models in measuring the productive efficiency of the electricity distribution sector.
Hall & Holmes, [93]; *IEEE*	2003	Developed an attribute selection technique for comparisons in Bioproducts.
Lagoe et al., [94]; *Nursing Economics*	1999	Presented benchmarking model using histograms on patient's length of stay in hospitals.
Burgess, [95]; *Journal of Operational Research Society*	1995	Discusses benchmarking as a technique that utilizes operational research (OR) principles to provide analysis of cultural dimensions for organizations.
Lorence, [96]; *Quality Progress*	1994	Discusses ten process and measurement areas that present opportunities for benchmarking in healthcare sectors.
Bell & Morey, [97]; *Omega*	1994	Proposed a macro analytical approach to selecting benchmarking partners utilizing allocative data envelope analysis.
Hequet, [98]; *Training*	1993	Discussed limitations to benchmark and emphasizes the need to be cautious against attempting to benchmark with large organizations that represent too large a gap in performance.
Schefczyk, [99]; *International Journal of Production Economics*	1993	Explores the use of productivity ratios, DEA, Spearman coefficient of rank correlation and linear regression analysis for performance analysis; The author concludes that simple cost-based measures are most appropriate for internal benchmarking.
Zairi, [100]; *Total Quality Management*	1992	Proposed the utilization of customer feedback in performance assessment during benchmarking. The authors encouraged the use of customer feedback to establish weaknesses in the levels of service offered in a company.

2.8. Benchmarking in Healthcare Sector

As stated earlier in chapter 1, this study focuses on the healthcare sector where benchmarking is looked at as performance measurement. Healthcare from literature studies is considered late in adopting and adapting quality assurance tools from other industries, but increasingly this is occurring Peek et al., [101]; Messahel & Al-Qhatani, [102]. Braillon et al., [103] reported the use of benchmarking in the healthcare sector was in 1990 by the Joint Commission on Accreditation of Healthcare Organization (JCAHO) in the United States. Some of these tools used by other industries include statistical process control and Six Sigma for identifying and reducing process variability; lean and constraint theory for improving efficiency by increasing throughput and/or reducing costs; Plan-Do-Check-Act which is used for process measurement; and benchmarking which allows organizations to compare the performance of their processes against their competitors. Authors have defined benchmarking in different ways, but the most acceptable definition given amongst them was Ellis, [5] who summarized benchmarking as a sustained effort to measure outcomes, compare the outcomes against others to learn how those outcomes were achieved, and apply the lessons learned to improve the healthcare system.

Increasingly, the need to deliver care at a low cost is resulting in greater focus on efficiency improvement. The challenge here lies in aligning the goals of cost reduction and quality improvement – an alliance that often seems counter-intuitive but has proven to be possible and fruitful [104]. In addition, tools such as electronic health records for collecting information and measuring health care performance are increasingly available. For institutions that have successfully achieved these goals, benchmarking performance against other institutions is the next step [104].

To implement benchmarking in the healthcare sector, researchers have stressed on the need for useful, reliable and up-to-date information [6]. This process of managing information is called *surveillance*. This is regarded as the first foundation of benchmarking, as it facilitates and accelerates the process. The second foundation includes learning, sharing information and implementing best practices to modify performance. Table 7 shows the existing work on benchmarking in the healthcare sector.

Table 7: *Review of Benchmarking in Healthcare Literature*

Author: Journal	Year	Method / Findings
El-Saed, et al., [105]; *Journal of Infection & Public Health*	2013	Proposed a theoretical framework for internal and external benchmarking of healthcare-associated infections; This framework included the use of multivariate analysis, stratification, indirect standardization, and restrictions.
Sobol & Prater, [106]; *International Journal of Healthcare Information Systems & Informatics*	2011	Utilized simple statistical tools such as mean, p-value, correlation to benchmark the use of information technology (IT) in U.S and Taiwan hospitals.
Kanerva, et al., [107]; *Journal of Antimicrobial Chemotherapy*	2011	Developed a framework for ranking hospitals based on performance using multivariate models and indirect standardization method for antibiotic use in different acute care hospitals.
Galterio, et al., [108]; *Journal of Healthcare Information Management*	2009	Suggested and outline the use of DEA as a new tool for benchmarking in hospitals to help in the normalization and standardization of performance.
Ellershaw, et al., **[109]**; *Support Care in Cancer*	2008	Applied questionnaires to evaluate the utility of participating in benchmarking project to assess the care delivered to

		patients in the dying phase; Simple statistical tools such as Likert scale, mean, and the median was utilized.
Earle, et al., **[110]**; *International Journal for Quality in Health Care*	2005	Utilized statistical tools to evaluate existing administrative data on the intensity of end-of-life cancer care; comparing the hospital data with different cancer treatment centers.
Wait & Nolte, **[111]**; *Benchmarking*	2005	Poses a question whether benchmarking initiatives are in fact guiding health policy towards the improvement of healthcare system performance
Hermann, et al., **[112]**; *Psychiatric Services*	2006	Statistical benchmarks such as Bayesian estimators and pared mean was utilized to measure the quality of care for mental and substance use disorders to identify high and low-performance areas amongst healthcare providers.
McLoughlin, et al., **[113]**; *International Journal for Quality in Health Care*	2006	Identified 21 usable set of patient safety indicators that will allow performance comparisons to be made; Also helps to improve quality in healthcare.
Schwappach, et al., **[114]**; *International Journal for Quality in Health Care*	2003	Statistical test such as unpaired t-tests, chi-square test, Mann Whitney test, fisher's test, and multiple logistic regression were used to assess the clinical performance and patients' experiences within the emergency department.
Pantall, [3]; *NT Research*	2001	Examines the process of benchmarking and the ways in which it can be used to secure improvement and best practice in the healthcare sector.
Burstin, et al., **[115]**; *The American Journal of Medicine*	1999	Proposed the use of linear and logistic regression to evaluate the effect of inter-institution benchmarking on several quality measures.
Yarnold, et al., [116]; *Journal of Behavioral Medicine*	1998	Employed hierarchically optimal classification tree analysis to obtain a nonlinear model for predicting overall patient (dis)satisfaction using attributes such as waiting time, doctors concern, nurses attitude etc. in the emergency department of an academic hospital versus a community hospital
Hall, [117]; *Hospital and Health Services Administration*	1996	Nursing/staff items, physician issues, and waiting time are key factors that drive satisfaction within an emergency department
Hansagi, et al., **[118]**; *Health Care Management Review*	1992	Studied patient satisfaction in the emergency department and reported it to be significantly low for patients with triaged nonurgent than among the immediate and urgent triage patients as their level of satisfaction was high.

2.9. Benefits of Benchmarking

Benchmarking helps create a competitive environment within an organization. The benefits of benchmarking include:

1. Gain an independent perspective about the companies is performing when compared to others in relation to the cost, profit margin, and other key performance indicators
2. Creation of knowledge package which can push forward the whole sector [85]
3. Clearly identifying specific areas for improvement

4. Prioritize improvement opportunities
5. Set performance expectations and targets
6. Monitor and manage the changes in the company

2.10. Machine Learning Algorithms

Machine learning algorithms (MLA) as defined by [119] are artificial intelligence technique that provides computers with the ability to learn without being explicitly programmed. The process of MLA is like that of data mining because both systems search through data for patterns. Data mining is the process of finding anomalies, patterns and correlations within large data sets to predict outcomes ML utilizes data to detect patterns and adjust program actions accordingly [120]. MLAs are categorized as supervised and unsupervised. Supervised algorithms use training data that is comprised of input data to learn about the target data. Unsupervised algorithms draw inferences from given datasets; the algorithm creates groups and subgroups within the data [121].

2.10.1. Review of Machine Learning Approaches

Various researchers have utilized the ML approaches in their application for the accurate learning of results. In this section, different ML approaches such as decision tree learning, artificial neural networks, deep learning, association rule mining, regression, Ensemble algorithms, support vector machines, clustering, inductive logic programming, Bayesian networks, reinforcement learning, representation learning, similarity and metric learning, dimensionality reduction algorithms, sparse dictionary learning, genetic algorithms, data envelopment analysis, rule-based machine learning and learning classifier systems are discussed.

Decision Tree: is a graph that utilizes a branching approach to illustrate possible consequences, including chance events, outcomes, resources costs, and utility to predict the outcome of a target. Examples of decision trees include classification and regression tree (CART), decision stump, C4.5 and C5.0, chi-squared automatic interaction detection (CHAID).

Neural Network Algorithm: are models that are inspired by the structure and function of biological neural networks. The computations are structured in terms of an interconnected group of artificial neurons. Examples include perceptron, back-propagation, Hopfield network etc.

Deep Learning: involves building much larger and complex neural networks and is focused on semi-supervised learning problems with large datasets containing very little labeled data. Examples include convolutional neural network (CNN), deep Boltzmann machine (DBM), deep belief networks (DBN) etc.

Association Rule Mining: This method extracts rules that best explain observed relationships between variables in a given dataset. Examples are Apriori and Eclat algorithm.

Support Vector Machine (SVM): are set of supervised learning methods used for classification and regression analysis. It is a discriminative classifier formally defined by a separating hyperplane.

Clustering: it is a method of unsupervised learning that is based on assigning a set of observations into clusters so that observations within the same cluster are similar according to a predesignated criterion. Popular clustering algorithms are k-Means, k-Medians, expectation maximization, and hierarchical clustering.

Bayesian Algorithms: These are methods that explicitly apply Bayes' theorem for problems such as classification and regression. It is a probabilistic model that represents a set of random variables and their conditional independencies using a directed acrylic graph (DAG).

Dimensionality Reduction Algorithms: is defined as the process of compressing and reducing the number of features in a dataset under consideration, by obtaining a set of principal variables. This helps in reducing computational complexity and overfitting of data. Some dimensionality reduction algorithms include principal component regression, principal component analysis, Sammon mapping, projection pursuit, linear discriminant analysis, flexible discriminant analysis etc.

Genetic Algorithm: it is a search heuristic that uses a process of natural selection and other methods such as mutation and crossovers to generate genotype in finding optimal solutions to a given problem [122].

Data Envelopment Analysis: it is a nonparametric linear programming method for measuring the efficiency of decision-making units by formulating a multidimensional input and output vectors.

Ensemble Algorithms: It is a technique that combines multiple MLA together that are trained independently and whose predictions are combined in some way to make an overall prediction. Some examples include boosting, AdaBoost, gradient boosting machines, random forest etc.

2.11. Gaps in Literature

From existing literature, many authors failed to use a systematic/structured benchmarking process that shows how data is collected, how analysis is conducted as well as recommend improvements and monitoring actions. It is vital to use a structured process as it shows clearly the areas of improvement. *Secondly,* there's a lack of statistical and analytical tools utilized and incorporated into benchmarking analysis. Most of the tools used are focused on performance monitoring rather than recommending and driving sustained improvements. *Thirdly,* due to heterogeneous nature of data available, most authors use a small dataset to develop their framework as they lack the required expertise in data analysis or proposed only a theoretical framework [105].

Burstin et al., [115] implemented benchmarking process using linear and logistic regression for analysis but this method failed as they were unable to replicate and generalize their approach to other hospitals and the data used was altered to suit their needs.

Kwon et al., [83] as seen in table 6, used a DEA-NN approach for analysis but failed to incorporate this into a structured benchmarking process. Also, Schefczyk, [99] utilized DEA for performance analysis and failed to incorporate it in a structured benchmarking approach.

Bereskie et al., [84], developed a framework for water quality assessment using a fuzzy-rule-based model. This approach is unique as it focuses on functional benchmarking to help owners, operators and planners of small drinking water systems in decision making. Limitations of this approach are its complexity and inability to be replicated to other sectors, also the framework depends significantly on the motivation of its users for establishing the fuzzy rules which result in improper weightings.

2.12. Research Contributions

This study contributes to knowledge by developing a unique and effective performance prediction model using MLA and integrating this model into a structured benchmarking process for comparative analysis. Secondly, this research is unique as it is the first to study and benchmark the performance and efficiency of the emergency department as other authors have studied only the efficiency of different hospitals and selected departments. This research fills the gap of providing a sophisticated statistical and analytical tool for analysis in a systematic benchmarking process. This tool can effectively analyze any type and size of dataset given. The outcome of this process is to enable identification of areas that need improvement based on performance, recommend, implement and monitor improvements in the areas studied.

CHAPTER THREE

3.0. Research Methodology

3.1. Introduction

This chapter discusses the methodology in detail which is applied to achieve the objective of the study in developing a four-phase systematic and structured benchmarking process that incorporates machine learning algorithms for analysis is presented in figure 9. An elaborate description of what each phase entails and steps are given in subsequent paragraphs.

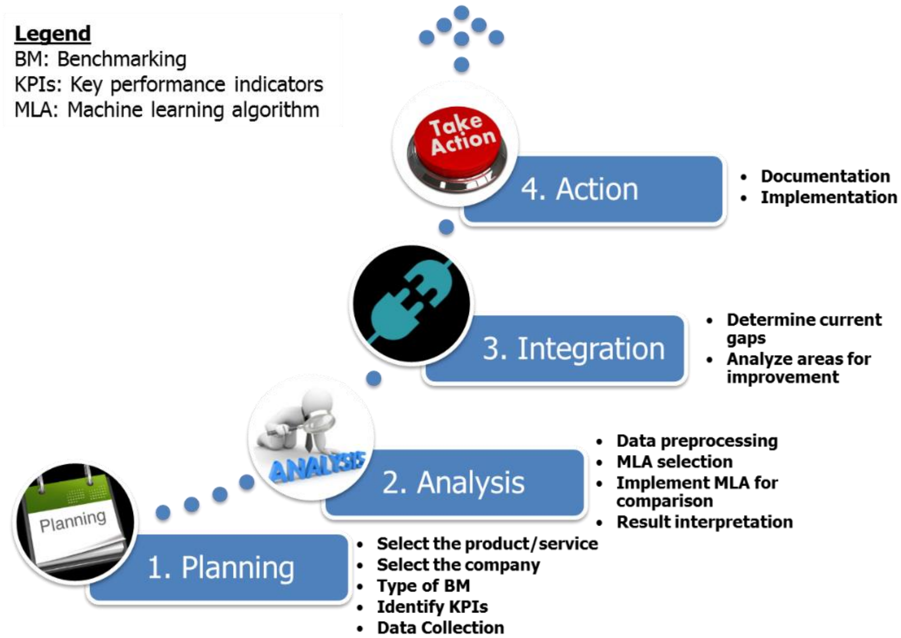

Figure 9: Systematic Benchmarking Approach Integrating Machine Learning Algorithm

3.1.1. Phase 1: Planning

This phase involves planning, identifying and defining as accurately as possible the product or service to be benchmarked. It is designed to develop the plan for conducting the benchmarking study. It forms the basis for the entire benchmarking process; therefore, every effort should be made to conduct this step as thoroughly as possible. During this phase, the organization needs to decide and select the processes, product or service it intends to benchmark, analyze the processes in detail, calculate the metrics and define their performance gaps, identify best practice partners, determine the mode of data collection and collect the required data. Incorrect identification at this stage could result in a waste of resources and improper result at the end of the study.

Step 1: Identifying the Product / Service – This involves selecting and identifying the product, process or service that is performing below the required target in an organization.

Step 2: Identify the company – This step is important due to the competitive nature of companies today. Most companies do not want to share their knowledge or data with competitors so as not to take their customers. Identifying the best in the business, who is willing to share information on how they are performing will go a long way to help other companies who are interested in conducting benchmarking.

Step 3: Type of benchmarking – This depends on what the company wants to measure. As stated in chapter 2, if internal benchmarking is selected, then departments within the same organization should be identified and selected for benchmarking. If it is external benchmarking, products or services offered by the company and a second company who is best in the business should be identified and benchmarked. This applies to functional and generic benchmarking. Most companies prefer to start with internal benchmarking as it shows them their strengths, performance, and weaknesses of the products, processes or services they deliver.

Step 4: Key performance indicators (KPIs) – This are set of quantifiable measures that a company uses to gauge performance over time [123]. These metrics are used to determine an organization's progress in achieving strategic and operational goals, and to compare a company's performance against others who are best in the business. This helps them to determine areas which they have been successful in and shows areas where they need to improve. KPIs differ from amongst industries.

It is important to state the four elements contained in an activity that is used in performance measurement. This includes input, output, activity, control, mechanism, control and time [124].

- Input indicates the resources required to enter an activity to produce an output
- Output captures the outcomes of an activity/group of activities
- Activity indicates the transformation produced while a function is being done
- The mechanism enables an activity to work

- Control is an object that controls the activity's production through compliance
- Time is a temporal element of an activity

Step 5: Data collection – This is a process of gathering and measuring information on targeted variables in an established and systematic way, which enables us to answer relevant questions and evaluate outcomes. Data is collected based on the selected KPIs in step 4. This can be qualitative or quantitative data depending on the organization or the benchmarking team. The data can either be gotten on a weekly, monthly or yearly basis which depends on the scope of the benchmarking project.

3.1.2. Phase 2: Analysis

This phase involves analyzing the benchmarking data to determine current performance gap and project future performance levels while identifying and understanding the practices which contribute to the best practice partners' strengths. According to Deros, et al., [123], some key questions to be answered during this phase are as follows:

- What's the performance level of the best practice partners?
- What's our performance compared to them?
- Why are they better?
- What can we learn from them?
- How can we implement the lessons learned into our company?

This phase is vital as it helps in determining the performance gap in the company. From literature, it is seen that most authors use simple statistical tools in this phase which is not sufficient for analysis and others skip the structured process and analyze only the data without showing how each step was carried out. While organizations who have amassed a ton of data do not have the required tools and expertise to carry out the analysis phase during a benchmarking project. This research focuses on the analysis phase where machine learning algorithms are used for comparative and predictive analysis of the benchmarking data. The *Open Source Data Envelopment software, OSDEA (http://opensourcedea.org)* and the *Waikato Environment for Knowledge Analysis, WEKA* software was utilized for analysis. This software's have a sophisticated graphical user interface which compiles and runs on a wide variety of UNIX platforms, Windows, and MacOS. Steps followed to achieve the analysis phase are outlined below;

Step 6: Data Preprocessing – The need to process data is now widely realized and reflected in every field of work [125]. This step is important as it helps in the conversion of data into a usable structure and format. It involves data organization, modification, storage and presentation of information in a usable format. The following process given by [126] is followed for preprocessing;

Stage 1 – Formatting: The collected data may not be a format suitable to work with. The data may be in a relational database or a proprietary file format, this must be converted to a flat file or text file for easy analysis.

Stage 2 – Cleaning: This is the elimination or fixing of missing data. There may be instances that are incomplete and do not carry the data needed. To solve this, we use a process called mean or median imputation to replace the data in the missing row or column of the given dataset. Also, there may be instances where sensitive information is contained in the data such as social security details, driver's license number etc. This information needs to be removed and a process called deidentification is used to anonymize the data.

Other preprocessing stages that can be carried out include;

Stage 3 – Scaling: The preprocessed data may contain attributes with a mixture of various quantities such as time, sales volume, weight etc. Many MLA like data attributes to have a scale between 0 and 1. So this stage is done to datasets with a mixture of different quantities.

Stage 4 – Decomposition: The data may contain features that represent a complex concept that may be useful to an MLA when decomposed into constituent parts.

Stage 5 – Aggregation: The dataset may consist of features that need to be aggregated into a single feature that would be meaningful during the analysis.

Step 7, 8 & 9: MLA Selection/Implementation – This step involves selecting the algorithm that would be used for performance prediction modeling of the benchmarking data. A hybrid algorithm which consists of data envelopment analysis (DEA) and back propagation neural network (BPNN) is selected. Details of this algorithms are given below.

3.1.2.1. *Data Envelopment Analysis (DEA)*

DEA is a methodology motivated by frontier methodology [127], [128] pioneered DEA research and developed the Cooper-Charnes-Rhodes (CCR) model [129] which was later modified by Banker et al., [130] into the Banker-Charnes-Cooper (BCC) model. DEA models utilize a nonparametric linear programming method for measuring the efficiency of decision-making units (DMUs) for formulating multidimensional input and output vectors [131],[132],[133]. DEA calculates the ratio of the weighted sum of inputs and the weighted sum of outputs of DMUs and identifies efficient units [83]. It envelops these data points while assigning fractional values to the remaining inefficient DMUs under the envelopment surface. It is an optimization tool that identifies best practices, measures the relative efficiency of DMUs, and determines the appropriate levels of variables for inefficient subgroups to achieve efficient status.

DEA models have two distinct orientations, input-oriented and output-oriented models. The input-oriented model is centered on the utilization of minimum resources while the output-oriented model is focused on maximum improvements of outputs given the assumption that the constant inputs are a primary concern. The selection of the orientation must be in accordance with the objectives and expected outcomes of the research [134]. The output-oriented model proposed by Emrouznejad & Shale, [134]is considered in this study because it expands the output of the DMUs within the production space. The formulation of the output-oriented model that represents the DEA frontier can be expressed as:

Model A

$$\max imize\ \text{h} \quad (1)$$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} + S_i^{+} = x_{ij0} \qquad \forall i \quad (2)$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - S_r^{-} = h y_{rj0} \qquad \forall \text{r} \quad (3)$$

$$S_i^{+}, S_r^{-} \geq 0 \quad \forall i, \forall r$$

$$\lambda_j \geq 0 \quad \forall j$$

Where

x_{ij} = amount of the *i*th input at each unit

y_{rj} = amount of output *r*th output from each unit

j_0 = the DMU to be assessed

λ_{j} = weight for unit *j*

h = output-oriented efficiency score

S_i & S_r = Slack variables for input *i* and output *r* respectively

n = number of DMUs

If h^* is the optimal value of *h*, then DMU_{j0} is said to be efficient if $h^* = 1$ and the optimal values of S_{r}^{+} and $S_{\text{i}}^{-} = 0$ for all *i* and *r*. The slack variable in an input *i*, $S_i > 0$ represents an additional inefficiency in the use of input *i*. The slack variable in the output *r*, $S_r > 0$ represents an additional inefficiency in the production of output *r*. The DEA method determines the positive weights set to maximize *h*, with the constraint efficiency scores ranging from 0 to 1. The process continues to find efficiency scores of DMU by solving *n* linear programs. The best practice DMUs with efficiency scores of 1 form the envelopment surface and is the benchmark for peer DMUs [135].

However, due to its nonparametric nature and capabilities of accommodating multiple inputs and outputs, DEA has been a popular tool in efficiency measurements [83]. Despite its strengths, DEA has some limitations;

1. It is very sensitive to the presence of outliers and statistical noise. Outliers can cause problems to the mean and increase the standard deviation during analysis leading to incorrect results.
2. Superiority-driven DEA solutions may not always be realistic or actionable even after admitting its soundness of the method
3. Lack of prediction capacity has been pointed out as a significant deficiency of the model that hinders further extension of the method of solving real-world problems [136],[137],[138],[139].

Exploiting the strengths of DEA while addressing its shortcomings, [140],[83] revealed that neural networks are an intelligent analytic tool for estimating the efficiency of DMUs.

3.1.2.2. *Artificial Neural Networks (ANN)*

ANN is one of the main tools utilized in machine learning. ANNs was developed to mimic the human nervous system. It extracts pattern from the observed data and the learns non-linear relationship between the input and output features. Learning is a key tenet for ANN and it is categorized as a supervised and unsupervised model depending on the presence of target variables in the dataset. Back-propagation neural network (BPNN) which is a supervised learning network is utilized in this study. BPNN is a systematic method for training multilayer neural network and provides a computationally efficient method for changing the weights in a feed-forward network, with differentiable activation function units, to learn a training set of input-output variables. BPNN is adopted due to its adaptive learning and nonlinear behavioral patterns of capturing the input and output data. As an adaptive learning technique, BPNN allows presentation of data to the model for an update of learned information which is encoded in weights connecting neurons in a highly parallel structure. It has a layered structure comprised of neurons in an input layer, hidden layer and an output layer (see *figure 10* for a neural network architecture).

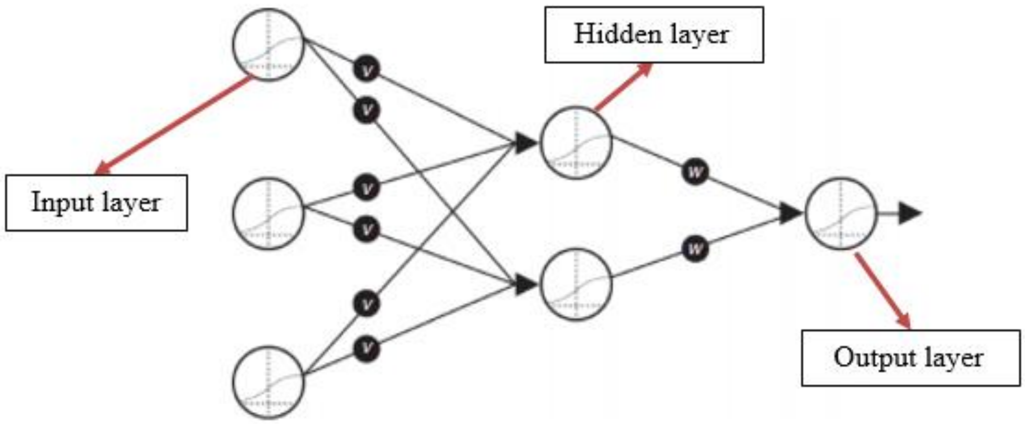

Figure 10: Neural Network Architecture (Source: Kwon, [129])

The training of BPNN involves three sequential methods: the forward propagation of the input, the back propagation of the error, and the adjustments of weights. The backpropagation learning algorithm is simply a gradient descent method which minimizes the sum of square errors [141],[142].

The computational formula and procedure for the standard backpropagation is given below:

$$Y_K = f(y_{netK}) = f(\sum_j H_j w_{jk}) \tag{4}$$

Where

Y_k = output of neuron k in the output layer

f () = arbitrary activation function to be applied to net output y_{netK}

H_j = input from hidden neurons

w_{jK} = weight between output neuron k and hidden neurons

The backpropagation of the error is given below:

$$E = 1/2 \sum_k [D_k - Y_k]^2 \tag{5}$$

Where

E = squared errors

D = target output

Y = activated network output

The adjustment of weights is given below which derived by applying chain rule:

$$\Delta w_{jk} = \rho H_j [D_k - Y_k] f^{'}(y_{netK}) \quad (6)$$

$$\Delta v_{ij} = \rho X_i f^{'}(H_{netj}) \sum_k \delta_k w_{jk} \quad (7)$$

Where

Δw_{jk} = weight change from hidden neuron j to output neuron k

ρ = learning rate

f' () = derivative of the activation function

Δv_{ij} = weight change from input neuron X_i to hidden neuron H_j

DEA and BPNN share some similarities as a nonparametric analytic tool. However, each method retains contrasting and complementary characteristics. DEA determines best practice DMUs and envelops extreme points as an optimization tool, while BPNN learns the central tendency of data by approximating the best fit as an adaptive learning model [143],[135],[144]. Therefore, exploring the advantages of these two approaches is enticing in that monotonicity-preserving DEA frontiers provides an outstanding condition for stable learning of BPNN. These two approaches are combined to form *Back-propagation DEA*.

3.1.2.3. *Back-Propagation DEA (BP-DEA)*

BP-DEA learns by iteratively processing a training sample, comparing the network's prediction of efficiency scores for each sample of DMUs with known efficiency scores. For each training sample, the weights are modified to minimize the mean squared error (MSE) between the network's prediction and actual efficiency score as obtained in a conventional DEA model. These modifications are made in the backward direction. The BP-DEA model is shown in figure 11 while the algorithm is presented in figure 12. The results derived are the efficiency of each DMUs which shows if they are performing well or not. A comparison of DEA and Neural Network for efficiency measurement adapted from Wu et al., [139] is presented in Table 8.

	Table 8: *Comparison of DEA and Neural Network for efficiency measurement [139]*	
	DEA	**Neural Network**
S/N	**Similarities**	
1	It is a non-parametric algorithm	It is a non-parametric algorithm
2	No assumptions about the functional form that links its inputs to outputs	No assumptions about the functional form that links its inputs to outputs
3	Optimal weights to maximize efficiency	Optimal weights to derive the best possible fit
4	Invariant to the units and scale	Scale preprocessing
	Differences	
5	It takes medium assumptions about the functional form and data	It takes low assumptions about functional form and data
6	Medium flexibility	High flexibility
7	Many theoretical studies/applications on efficiency	Few theoretical studies on efficiency
8	Low cost of software and estimation time	High cost of software and computational time

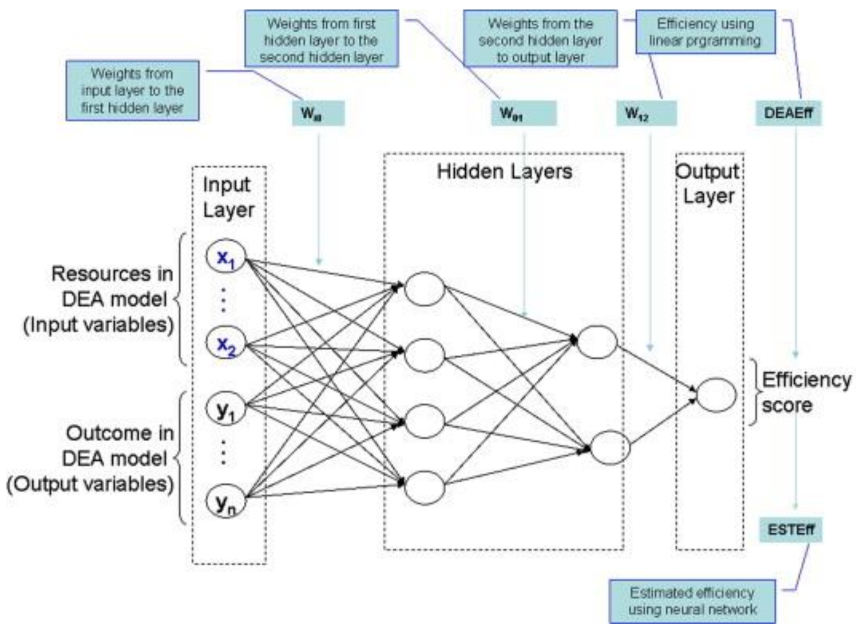

Figure 11: BP-DEA model (Source: Emrouznejad & Shale, [134])

Back-propagation DEA algorithm

1) Initialize all weights // usually to small random numbers //
2) While terminating condition is not satisfied {
3) For each training sample of DMUs in samples
{
4) For each hidden layer neuron j
{
// note that for resource variables $x_1 \ldots x_n$ and
// outcome variables $y_1 \ldots y_n$ the $O_k = I_k$, θ_k is bias //
5) $I_j = \sum_i w_{ij} O_j + \theta_j$
6) $O_j = 1/(1 + e^{-I_j})^{-1}$;
}
7) $Err_j = DEAeff_j\,(1 - DEAeff_j)\,(ESTeff_j - DEAeff_j)$
// $DEAeff_j$ is the efficiency as obtain from DEA
// $ESTeff_j$ is the efficiency as estimated by neural network
8) For each unit j in the hidden layers
9) $Err_j = O_j(1 - O_j) \sum_k Err_k w_{jk}$;
10) For each weight w_{ij} in network
{
11) $\Delta w_{ij} = (l)\, Err_j \times O_j$;
12) $w_{ij} = w_{ij} + \Delta w_{ij}$;
}
13) For each bias θ_j in network
{
14) $\Delta \theta_j = (l)\, Err_j$
15) $\theta_j = \theta_j + \Delta \theta_j$;
}
16) }
17) }

Figure 12: BP-DEA Algorithm (Source: Emrouznejad & Shale, [134])

3.1.3. Phase 3: Integration

The objective of this phase is to develop goals and integrate them into the benchmarked process so that significant performance improvements can be achieved. Some questions as suggested by [123] that needs to be answered in this phase include:

1. Has management accepted the benchmarking findings?
2. Based on the findings does the company need to adjust its goals?
3. Have the goals been clearly communicated to all relevant parties involved?

Step 10 & 11 looks at identifying the gaps in the departments with low efficiency/performance from the analysis and recommending ways for improvement by studying the areas with high performance. Establishing goals that will help the organization improve its performance is vital.

3.1.4. Phase 4: Action

Action plans need to be developed to achieve the goals decided upon in phase 3. Steps 12 &13 involves documentation of the benchmarking study, the implementation of necessary actions, and monitoring the progress. Also, the use of a continuous improvement tool such as *PLAN-DO-CHECK-ACT (PDCA)* to constantly monitor the performance of the organization is necessary.

CHAPTER FOUR

4.0. Case Study

The data from the Emergency Department (ED) at Henry Ford Hospital, Detroit is collected for analysis and verification of the proposed methodology.

Henry Ford Hospital (HFH) is an ultramodern, 877-bed tertiary care hospital, education and research center located in Detroit’s New Center area, Detroit, Michigan. The hospital is known for clinical excellence in the fields of cardiology and cardiovascular surgery, neurology and neurosurgery, orthopedics, multiorgan transplantation, and the treatment of prostate, breast and lung cancer. It is the front-runner of the Henry Ford Health System (HFHS), one of America’s leading comprehensive integrated health systems. The hospital is staffed by the Henry Ford Medical Group, one of the nation’s biggest and oldest group practices, with an estimate of 1,200 physicians and researchers in more than 40 specialties who staff HFH and 29 Henry Ford medical centers [145].

For more than 100 years, HFH has been a leader in advancing medicine and delivering the most innovative treatments. People travel to HFH from throughout the United States and its environs for specialized care and treatment. The hospital care system consists of full medical care which includes inpatient and outpatient care. Some of the health services performed by HFH includes cancer therapy and services, dermatology services, heart and vascular services, laboratory services, walk-in/urgent care services, primary care and emergency care services etc.

Currently, the hospital is seeking to improve the performance of the ED as well as measure the efficiency of the department due to challenges faced with high patient boarding rates. This issue has led to low quality of healthcare service being delivered, patients leaving the ED without being seen, the spread of contagious disease, and financial implications on the hospital. Four sub-departments of the ED are selected and performance measurement data of the departments for the year 2017 is collected for benchmarking analysis. These departments are:

1. The Critical Care Department (Denoted as *CAT 1*): It deals with the specialized care of patients whose conditions are life-threatening and who require comprehensive care and constant monitoring, usually in the intensive care units. Examples of patients treated in this department are accident victims, victims of shootings, and disasters. Most of these patients are brought via the emergency medical services [120].
2. The Medium Acuity Care Department (Denoted as *CAT 2 East Wing*): The patients in this area are acutely ill but do not have an immediate life threat and do not require continuous monitoring.
3. The Medium Acuity Care Department (Denoted as *CAT 2 West Wing*): The patients in this area are acutely ill but do not have an immediate life threat and do not require continuous monitoring.
4. The Pediatrics and Urgent Care Department (Denoted as *CAT 3/4*): This area is primarily used to treat patients who have an injury or illness that requires immediate care but isn't serious enough to warrant a visit to a hospital emergency room. Examples of patients treated here are patients with cuts, bruises, fever etc.

Six input measures and four output measures within the emergency department’s control were selected to measure the efficiency for each of the departments described above. The input measures are total volume of patients in the ED, door to room time, door to doctor time, total number of patients, door to disposition time, total number of patients admitted whereas the output measures are the ED length of stay (LOS), disposition to departure time, admit LOS, and disposition to admit time.

CHAPTER FIVE

5.0. Results & Discussion

5.1. Introduction

This chapter discusses the results of the benchmarking analysis applying the proposed methodology described in chapter 3 on the case study presented in chapter 4. The results will be discussed based on the four phases of the structured benchmarking process.

5.1.1. Phase 1 – Planning Results

Step 1: Identifying what to benchmark – In this step, the performance and efficiency level of the health care services delivered by the emergency department (ED) is identified for benchmarking based on the hospital management's decision to improve the performance of the ED which is affected by high patient boarding rates. Patient boarding rate is the practice of keeping patients in the ED after they have been admitted to the hospital because no inpatient beds are available. This practice often results in several problems, including ambulance refusals/diversion, prolonged patient waiting times, and increased suffering for those who wait, lying on stretchers in ED corridors for hours, and even days, which affects their care, comfort and the primary work of the ED staff taking care of ED patients. This leads to low patient satisfaction and financial implications on the hospital.

Step 2: Identifying the company to benchmark – Henry Ford Hospital, located in Detroit's New Center area, Detroit, Michigan is identified for benchmarking studies. This hospital is selected based on the challenges it currently faces on high patient boarding rates in its EDs which has resulted in poor performance and low efficiency of the department.

Step 3: Type of benchmarking – Based on the scope of the research, the internal benchmarking method was selected. From literature, it is recommended that the best type of benchmarking to start with for hospitals are internal benchmarking, as this helps to know the hospital's strengths and weaknesses within its departments before proceeding to benchmark the hospital against its competitors. The ED at Henry Ford Hospital is divided into four sub-departments (*as stated in chapter 4*) and the description of the health care services provided is given in table 9.

Table 9: Description of the health care services provided by the Sub-EDs	
Sub-EDs	**Descriptions**
CAT 1	It deals with the specialized care of patients whose conditions are life-threatening and who require comprehensive care and constant monitoring, usually in intensive care units.
CAT 2 East Wing	The patients in this area are acutely ill but do not have an immediate life threat and do not require continuous monitoring.
CAT 2 West Wing	The patients in this area are acutely ill but do not have an immediate life threat and do not require continuous monitoring.
CAT 3/4	This department focuses on treating patients who are injured or ill and require immediate care but isn't serious enough to warrant a visit to a hospital emergency room.

Step 4: Identifying key performance indicators (KPIs) – This is a measure used to track an organizations success. Different KPIs are identified and selected from the ED (see table 10) to enable us to measure the efficiency and performance of the department. This KPIs are selected based on the metrics that are being controlled and measured within the ED at the Henry Ford Hospital.

Table 10: *Selected KPIs from the ED*	
KPIs	**Definitions**
Total Volume	This is the number of patients brought via ambulance or walk-ins into the ED of the hospital that require care.
Door to Room	It is the time (in minutes) elapsed between patient's "signed in" to the ED to be seen, and that patient's being placed in any ED room/bay.
Door to Doctor	The time difference in minutes between arrival time and doctor contact with the patient.
Number of Patients	The number of patients present in the ED within a given period.
Door to Disposition	The number of minutes that have passed between the patient's arrival and being placed in a patient care area.
Total Admit	The total number of patients admitted into the various departments in the hospital from the ED.
ED length of stay (LOS)	The arrival time (in minutes) of a patient to the ED and the departure time (in minutes) of the patient from the ED.
Disposition to Departure	It is the consequent event ending a patient's encounter in the ED leading to departure (in minutes).
Admit LOS	The time difference in minutes between arrival time and physical departure of the patient from the ED treatment area.
Disposition to Admit	It is the consequent event ending a patient's encounter in the ED leading to the patient being admitted to the hospital.

Step 5: Data collection – Data is collected based on the selected KPIs from the ED. The data is gathered from the hospital's electronic health record (EHR) system for each of the sub-EDs. The study period was from January 2017 to December 2017.

5.1.2. Phase 2 – Analysis Results

Step 6: Data preprocessing – The data is gathered in an excel sheet and was not in a usable structure for analysis without first converting it to a .csv file format. The dataset is cleaned, analyzed for errors and missing values using the WEKA software. A total of 60 data points were missing from the dataset and the *ReplaceMissingValue* function on WEKA which uses the mean imputation was utilized to fill in the missing values. The total patient's visit was 97,269 and 18,171 patients were admitted into the different sub-EDs. A summary of the statistical properties of the dataset for the four sub-EDs considered in this study is presented in Table 11.

Table 11: *Summary of Statistical Properties of the Data for the 4 Sub-EDs*

Data	Minimum	Maximum	Mean	Standard Deviation
Total Volume	0	2624	1974.98	560.94
Door to Room	18	44	30.08	7.29
Door to Doctor	29	82	51.85	19.92
No of Patients	1199	2624	2026.438	481.18
Door to Disposition	133	336	262.21	70.82
Total Admit	0	1396	378.56	561.22
ED Length of Stay (LOS)	151	483	328.43	102.54
Disposition to Departure	17	176	58.56	50.82
Admit LOS	0	537	118.98	209.01
Disposition to Admit	82	267	177.39	39.19

Step 7, 8 & 9: MLA Selection, Implementation, and Result Interpretation – The proposed performance prediction model discussed and selected in chapter 3 is utilized for analysis. First, the data is inputted into the OSDEA software to determine the efficiency of each decision-making units (DMUs) which are the sub-EDs. Figure 13 depicts the BP-DEA architecture utilized for the analysis in this step. Table 12 presents how the KPIs are divided into input and output variables for DEA efficiency analysis.

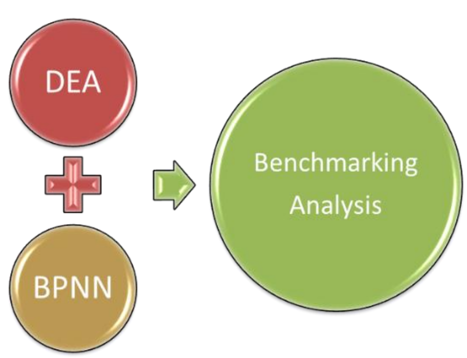

Figure 13: BP-DEA Architecture

Table 12: *Input and Output Variables for DEA Efficiency Analysis*

Input Variables	Output Variables
Total Volume	ED Length of Stay (LOS)
Door to Room Time	Disposition to Departure Time
Door to Doctor Time	Admit LOS
No of Patients	Disposition to Admit Time
Door to Disposition Time	
Total Admit	

The following are the model details selected for analysis in the OSDEA software;

1. Model Type: Banker-Charnes-Cooper (BCC) Output model. This model was first introduced in 1984 to introduce *Variable Returns to Scale* because the CCR model only assumed *Constant Returns to Scale*. The only difference with the CCR model is the convexity constraint e*Lambdas = 1 / or u_o in the multiplier form (see model A in chapter 3).
2. Model Characteristics:
    a. Output Oriented
    b. Technical Efficiency
    c. Variable Return to Scale

The results from the DEA analysis is presented in table 13. As seen in Model A in chapter 3, if the optimal solution h^* is the optimal value of h, then DMU_{j0} is said to be efficient if $h^* = 1$ otherwise it is inefficient and the optimal values of the slack variables, S_r^+ and $S_i^- = 0$ for all i and r. The slack variable in an input i, $S_i > 0$ represents an additional inefficiency in the use of input i. From the results, *CAT 1* has an efficiency score of 98%, *CAT 2E* has an efficiency score of 98.4%, *CAT 2W* has an efficiency score of 96.1% and *CAT 3/4* has an efficiency score of 97.7%. It is inferred from the results that none of the DMUs are efficient. This could be because of statistical noise and outliers in the dataset. Statistical noise and outliers are the major limitations of DEA. To handle this, the second algorithm which is the *back-propagation neural network (BPNN)* is used to train and predict the efficiency scores obtained from the DEA analysis as well as provide new efficiency scores based on the input and output variables utilized in DEA. It can be said that DEA was used to provide class labels (efficiency scores) to each DMU which was originally unsupervised transforming it to supervised. This enables BPNN to train and predict each DMU in the dataset since the efficiency scores are the class labels.

Table 13: *DEA Efficiency Output for each DMU*		
DMUs	**Efficiency Score**	**Status**
CAT 1	0.980	Inefficient
CAT 2E	0.984	Inefficient
CAT 2W	0.961	Inefficient
CAT 3/4	0.977	Inefficient
Note: *Efficient DMU = 1; Inefficient DMU = <1*		

Table 14 presents the parameters of the estimated BPNN. The multilayer perceptron is used for the analysis in WEKA software. A percentage split is used to divide the dataset for training, testing, and validation. Some functions used to fine tune the dataset are the *nominalToBinaryFilter*, *normalizeAttributes*, and *normalizeNumericClass*.

The *nominalToBinaryFilter* – this will preprocess the instances with the filter. This could help improve the performance if there are nominal attributes in the dataset.

The *normalizeAttributes* – this will normalize the attributes. This could help the improve performance of the network. This is not reliant on the class being numeric as it will also normalize nominal attributes as well (after they have been run through the nominal to binary filter if that is in use) so that the nominal values are between -1 and 1.

The *normalizeNumericClass* – this will normalize the class if it's numeric. This could help the improve performance of the network, it normalizes the class to be between -1 and 1. Note that this is only internally, the output will be scaled back to the original range. Figure 14 shows a visual diagram of the network topology. The network uses the DEA input and output variables as input and the DEA efficiency scores as the output.

Table 14: *Estimated Back-Propagation Neural Network Parameters*	
Concept	Result
Network Architecture	Multi-layer Perceptron (Back-Propagation)
Number of neurons: input-hidden-output	10 – 45 – 1
Number of layers	1 – 3 – 1

Activation function (hidden/output)	Sigmoid
Learning rate	0.8
Epoch	500
Momentum	0.6
Percentage Split	Training: 60%, Testing: 30%, Validation: 10%

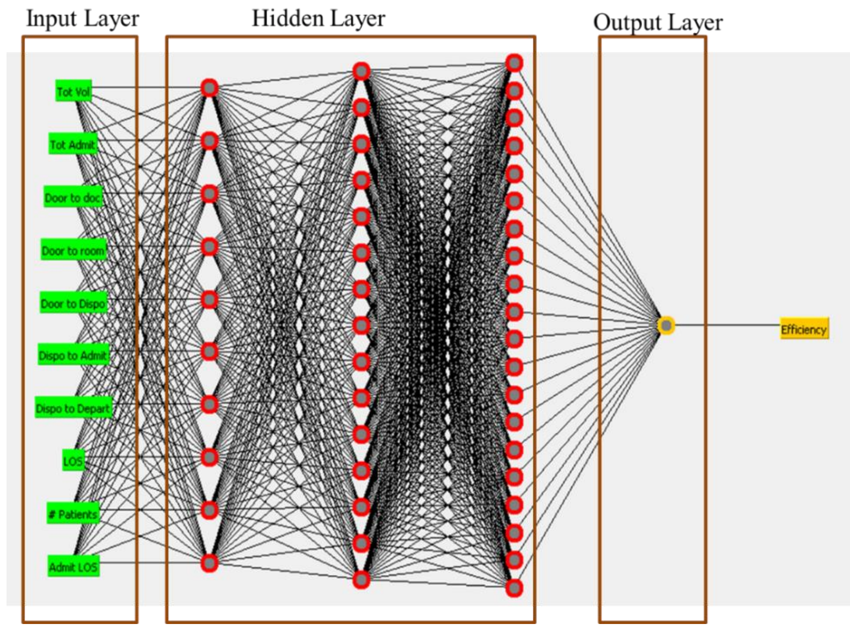

Figure 14: BP-DEA Network Topology

Table 15 demonstrates the predicted efficiency scores obtained from the proposed BP-DEA model. The results reveal that some of the DMUs have efficiency scores of 1 because neural networks use the stochastic properties to construct the frontier of efficient DMUs. *CAT 1* and *CAT 3/4* are inefficient with an efficiency score of 99.08% and 97.6% respectively. *CAT 2E* and *CAT 2W* are efficient with an efficiency score of 100% respectively. We can infer that the same processes are performed in *CAT 2E* and *CAT 2W* since their efficiencies are the same. With this, we would focus on improving the efficiency of *CAT 1* and *CAT 3/4* as the analysis shows that the processes performed in this department are leading to poor performance. A careful study of the processes performed in *CAT 2E* and *CAT 2W* will be carried out and used to proffer solutions to *CAT 1* and *CAT 3/4* experiencing low performance. In other to validate the results obtained from the neural network, some test statistics such as the correlation coefficient, root mean squared error is computed (see table 16).

Table 15: *BP-DEA Results from WEKA*

DMUs	Efficiency Score	Status
CAT 1	0.9908	Inefficient
CAT 2E	1	Efficient
CAT 2W	1	Efficient
CAT 3/4	0.976	Inefficient
Note: *Efficient DMU = 1; Inefficient DMU = <1*		

The results of the test statistics, for correlation coefficient, indicates that there is a linear correlation between the variables in the dataset while the root mean squared error shows that the error between the dataset is very low and it is close to fitting the actual model to the predicted model.

Table 16: *Summary of Test Statistics*	
Correlation Co-efficient	0.2649
Mean Absolute Error	0.0322
Root Mean Squared Error	0.0366
Relative Absolute Error	133.02%
Root Relative Absolute Squared Error	128.05%

A comparison of the DEA efficiency scores to the predicted efficiency score obtained using the proposed BP-DEA model is presented in figure 15 for each of the DMUs studied. It demonstrates that the predicted scores are above the actual scores for *CAT 1*, *CAT 2E* and *CAT 2W*. While the reverse is the case for *CAT 3/4*. This indicates that the predicted efficiency scores are a good proxy to basic DEA efficiency scores.

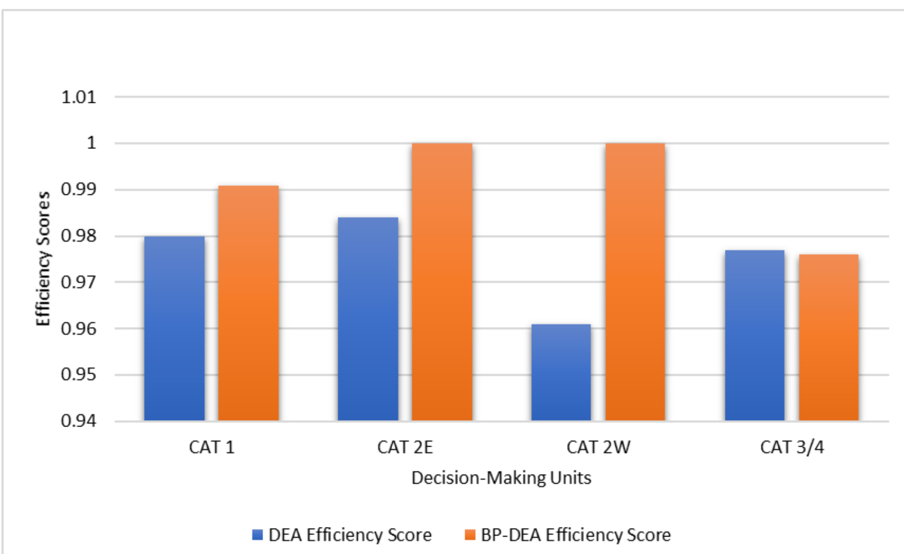

Figure 15: Actual Efficiency Score vs Predicted Efficiency Score

5.1.3. Phase 3 – Integration Results

Step 10: Identifying the gaps – From the results in table 15, it is seen that *CAT 1* (the critical care department) and *CAT 3/4* (the pediatrics and urgent care department) are inefficient from the BP-DEA analysis. This step identifies the gaps in this two departments that are causing it to have low efficiency/performance.

Current Gaps in CAT 1 (The Critical Care Department)

1. Information gap: Time is wasted collecting information from the patient when information is not readily available to the physician after the patient arrives the ED. This often occurs when patients arrive the ED in an ambulance with high illness severity or conditions and are not able to give appropriate personal information. This increases the patient's length of stay (LOS) in the hospital.
2. High delays at each point of treatment during patient flow in the ED resulting in bottlenecks. When there is a delay it prolongs the patient's LOS as well as affects those awaiting admission.
    - Patient flow is the movement of patients through the healthcare system.
3. Operational inefficiencies
    - Inpatient bed capacity: Due to unavailability of beds in the intensive care units (ICU), this leads to patient boarding.
    - Scheduling of surgeries and support staff.
    - Lack of adequate space in the ED to permit evaluation and treatment of patients.
4. Lack of information sharing between EMS and hospitals regarding overloaded EDs and availability of beds.
5. Overuse of ED services because of unnecessary referrals from physicians at small clinics has led to overcrowding.
6. Uninsured patients seeking care are the highest number of people found in the ED

7. Patient arrival times against staffing levels are not effectively and efficiently managed. This occurs because the right number of staffs are not available to treat the volume of patients at peak hours to avoid queueing and overcrowding.

Current Gaps in CAT 3/4 (The Pediatrics and Urgent Care Department)

1. High wait times for laboratory and radiology test results
    - Physicians must wait for lab test before treatment can continue and this affects patient flow and causes delays in the ED
2. High patient wait-times (an average of 40 minutes to see the doctor) especially for those arriving for minor illnesses.
    - Within the pediatrics department, non-urgent conditions account for 58 – 82 % of all visits.

Step 11: Analyze areas for improvement – improvement suggestions based on findings from the ED's with high performance is presented below;

1. Immediate bedding: This bypasses the triage process and places patients in beds as soon as they arrive when beds are available in the ICU. If No beds are available then a team triage is performed, where the nurses and physicians do an initial patient screening together in a triage room. This is considered a fast track approach as the patients are taken to a care space, acute-care bed or results pending area [146], [147].
2. Hold planning sessions to avoid delays in any of the shifts: Regular planning sessions should be done, and everyone included in planning the activities of the ED. The following should be done at the;
    a. Beginning of the shift
        - Avoid taking more than 2 to 3 sign-outs
    b. End of shift
        - 90 minutes left: Begin expediting admissions (e.g. some laboratory test is incomplete but unlikely to impact disposition, so advise the admitting physician of outstanding items)

- Make phone calls early (e.g. admissions, outpatient follow-ups). This is very important as it helps increase patient satisfaction and patients can give feedback on their treatments.
- 60 minutes left: Attempt to see easy dispositions one or two at a time.

3. Increase communication within the ED: Feedback from staff, nurses and physicians should be collected daily to monitor changes on how different processes are working.
4. Increase communication with the EMS: This is to ensure that the emergency ambulance do not bring patients to hospitals when the ED is overcrowded as this worsens the conditions of the patients and adequate care is not provided to them on time.
5. Avoid holding pattern test: This are ordered test (often carried out in complex cases) to defer your disposition decision or decisions to order advanced imaging, but they add little to no value to your decision-making process.
6. Executing decisions on time: This is the most valuable commodity in the ED as it helps with disposition
7. The laboratory testing and radiology department should be connected to the same EHR system so that once the patient data is inputted in the system at the ED, the testing can begin. This reduces delays in test results.

5.1.4. Phase 4 – Action Results

Step 12 & 13: Action plans, documentation and implementation – Some suggested action plans that needs to be implemented are described in this step to enable the emergency department to improve on its efficiency/performance. When implemented, the action plans will help improve the services provided by the hospital by decreasing the patient boarding rates, decrease patient wait times, reduce the number of patients leaving the hospital without being seen etc. This action plans include;

1. Integrating the laboratory and radiology department into the EHR system for better data handling and reduce wait time of test results.

2. Make available data on the capacity of EDs to EMS to ensure that patients are not brought to the EDs when it is full.
3. Staff education and culture change to ensure that whatever activity is implemented during the planning phase, everyone sees to it.
4. Creating reminder systems
    a. To alert staffs, nurses and physicians of weekly targets to reduce the time spent by patients in receiving treatments in the ED.
5. Adjusting the hours of operation to effectively ensure that adequate staffs, nurses and physicians are available during peak hours.
6. Establishing a bed-management system to identify and proffer solutions to bed-management problems
    a. This management will set up policies and framework for management of beds in the EDs and ICUs.
    b. Integration of a flexible bed base to always meet the fluctuating demands of the ED.
    c. Ensures that patients are admitted to their correct specialty ward/unit on admission or within 24 hours where appropriate.
    d. Ensure that accurate real-time information on the availability of beds is provided to the EDs.

The findings from the benchmarking analysis is documented and presented to management for approval and implementation. Monitoring of the implementation actions for successful execution and continuous improvement. Continuous improvement strategies must be implemented such as *plan-do-check-act* (PDCA) to properly monitor the improvement in the ED.

CHAPTER SIX

6.0. Conclusion

In this research, different quality improvement tools have been discussed with emphasis on benchmarking. Benchmarking has become necessary for any organization wanting to improve its products, processes or services to better serve customers and improve business results. Especially best practice benchmarking will be a strategic improvement need for organizations as it pursues to find and emulate best practices wherever they exist to close the gap and attain superiority [78]. Benchmarking practices often involves a quantitative and qualitative approach which demands managerial intuitions, often without the appropriate expertise.

A structured and systematic benchmarking model which consists of four phases namely; planning, analysis, integration and action phase has been presented. This model integrates machine learning algorithms as a performance prediction tool (BP-DEA) for benchmarking analysis. This fills the existing gap where authors have used simple statistical tools such as regression, bar charts, and histogram for analysis while other authors carry-out performance measurement in an unstructured way. As stated earlier, BP-DEA is utilized as the performance prediction tool in the benchmarking analysis phase.

DEA is a popular benchmarking tool used for performance measurement, it has been utilized mainly to identify best practice peers and to set optimal improvement goals [83]. DEA is a superiority-driven tool which has some limitations such as being prone to statistical noise, outliers and it lacks an adaptive prediction capacity. Identifying actionable peers from benchmarking studies and setting actionable goals are practical necessities that are more feasible than targeting admirable peers with ambitious goals in pursuit of improvement. To cater for the limitations of DEA, back-propagation neural network (BPNN) is utilized. BPNN is an intelligent analytic tool which has a parallel structure with interconnected neurons inspired by the human nervous system. BPNN learns abstract information from a limited source of data using an adaptive error minimization process through a gradient search method, and final weights retain key codes to retrieve a functional approximation for a set of given data [83].

This study proves effective in the application of the proposed approach in the healthcare industry using reliable data composed of four sub-EDs from a selected hospital in Michigan in 2017 as a case study. The analysis results suggest that, despite many efforts to improve healthcare efficiency in the ED of hospitals, there is much room for improvement, as the hospital's management has adopted the use of benchmarking to evaluate and monitor the performance and efficiency of the ED. The efficiency scores from DEA reveals that none of the DMUs which represents sub-EDs (*CAT 1: 98%, CAT 2E: 98.4%, CAT 2W: 96.1%, and CAT 3/4: 97.7%)* are inefficient under the BCC output model. Utilizing BP-DEA to train and predict the efficiency scores using the input and output variables from DEA the results obtained are *CAT 1: 99%, CAT 2E: 100%, CAT 2W: 100%,* and *CAT 3/4: 97.6%.* It concludes that *CAT 2E and CAT 2W* are efficient while *CAT 1 and CAT 3/4 are inefficient.* Some test statistics such as the correlation coefficient and the root mean squared error are used to validate the BP-DEA analysis which shows that the results obtained are robust.

Based on the results, the gaps in this two inefficient sub-EDs that are causing it to have low efficiency/performance are investigated. These gaps include lack of information between EMS and EDs, inadequate bed management, high delays at each point of treatment, high wait times for laboratory and radiology test results. Studying the departments with high performance levels, some significant processes where observed such as immediate bedding of patients; holding regular planning sessions; adequate communications with EMS; a connected laboratory testing and radiology department in the EHR system.

Action plans have been suggested to the hospital's management to be gradually implemented which will help improve the performance/efficiency of the ED. These plans include;

- Integration of laboratory and radiology department into the EHR system for *CAT 1* and *CAT 3/4.*
- Make available real-time data of hospital's ED capacity daily to EMS operatives.
- Proper staff education and sensitization on the new processes being put in place.
- Establishing a bed-management system for effective and efficient control of the beds in the EDs and ICUs.

Lastly, a continuous monitoring system is put in place which is the plan-do-check-act (PDCA) to ensure that the benchmarking process is utilized in an appropriate manner and the improvements in the ED is continuously monitored. The implementation of the proposed action plan leads to increased efficiency in operations, reduction in patient boarding rates, increased patient satisfaction, increasing hospital brand trust, reducing cost and waste in clinical resources as well as improving healthcare service delivery provided in the selected hospital's emergency departments. Also, the performance and efficiency of the department's increases. To the author's knowledge, this study is the first attempt to apply a BP-DEA in a systematic and structured benchmarking model.

This research is not free of criticism. The input variables were limited to the variables controlled by the ED which include the total volume of patients in the ED, door to room time, door to doctor time, the total number of patients, door to disposition time, and the total number of patients admitted. There could be many more factors beyond those variables. Future studies will pay attention to other important input variables not controlled by the ED. Secondly, another promising research avenue is to explore and compare the removal of outliers from the data set and use only DEA for performance measurement without the use of a neural network. Thirdly, conducting a voice of customer analysis to analyze how patient satisfaction affects the performance of the ED in benchmarking. Finally, how does the physical infrastructure of the ED affect its efficiency? The novel approach explained in this study can also be tested and adapted to datasets from other industries with slight modifications. It is desirable to work with companies and suggest better practice goals to improve their products, processes or services.

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ABSTRACT

THE IMPACT OF MACHINE LEARNING ALGORITHMS ON BENCHMARKING PROCESS IN HEALTHCARE SERVICE DELIVERY

by

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Currently, organizations have adopted and implemented a variety of innovative quality management philosophies, approaches, and techniques to stay competitive in an ever-changing global economy. Benchmarking is one of such techniques deployed by organizations to stay competitive. The motivation for this research stems from a real-world problem being faced by hospitals in the healthcare industry who have amassed a ton of data and want to embark on benchmarking project to assess the performance of the emergency departments due to challenges faced with poor management of operations which has led to high patient boarding rates, high patient wait-times, poor quality service, low patient satisfaction, and increased waste in clinical resources.

This study utilizes a unique structured and systematic benchmarking model which integrates machine learning tools such as data envelopment analysis and back-propagation neural network algorithms in analyzing and providing insights into the performance data collected from four selected emergency departments within a one-year period is presented. Data envelopment analysis (DEA) is a nonparametric approach in operations research for the estimation of production frontiers. Back-propagation neural network (BPNN) is an algorithm for supervised learning of artificial neural networks using gradient descent. The results obtained from the analysis shows that the integration of BP-DEA as a sophisticated performance prediction tool for analysis supersedes the utilization of simple statistical tools generally adopted by authors

for benchmarking studies. Our analysis further presents the efficient and inefficient departments and areas for improvement in the inefficient departments are investigated.

Recommendations are suggested based on the findings which when implemented leads to increased efficiency in operations, reduction in boarding rates and increased quality of healthcare services provided in the emergency department.

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