American Academic Scientific Research Journal for Engineering, Technology, and Sciences
ISSN (Print) 2313-4410, ISSN (Online) 2313-4402
https://asrjetsjournal.org/index.php/American_Scientific_Journal/index

Reliability Optimization in Healthcare Warehouses Through Advanced Quality Assurance Techniques

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Abstract

"Big data" refers to extremely useful and extensive datasets. A lot of people have been paying attention to it over the last 20 years because of the promising future it holds. The goal of many public and private organizations is to improve customer service by the collection, storage, and analysis of massive volumes of data. The healthcare business extensively uses big data from a wide variety of sources, including patient medical records, test results, hospital records, and Internet of Things devices. Additionally, biomedical research generates a substantial quantity of big data that is relevant to public healthcare. Proper management and analysis of this data are prerequisites for extracting actionable insights from it. This is crucial because without it, using big data analysis to solve problems is like trying to find a needle in a haystack. The only way to overcome the many challenges of processing massive data at each phase is to use state-of-the-art computer tools for big data analysis. For this reason, healthcare professionals who wish to propose solutions that can enhance public health must possess the appropriate infrastructure to methodically generate and evaluate large data. When big data is properly managed, analyzed, and understood, it can open up new possibilities for modern healthcare. That is why numerous industries, healthcare included, are putting in a lot of effort to make the most of this chance and transform it into better services and more money. Medical therapy and personalized treatment stand to benefit greatly from the current healthcare industry's increased emphasis on biomedical data integration.

Keywords: Big data; Quality Assurance Techniques; Healthcare; Warehouses; Reliability.

1. Introduction

Collecting data is an essential component for every organization because of this reason. In addition, we can make use of these data to forecast developments in the future as well as existing trends. We have begun producing and collecting more data about nearly everything by introducing technical improvements in this regard. This is because we are getting more and more aware of this at the same time.

Received: 3/16/2024
Accepted: 5/16/2024
Published: 5/26/2024
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It seems like we're amid a data deluge that covers every part of our lives, from our social lives to our scientific pursuits, our careers, and even our health.We can think of the current scenario as being similar to a flood of information. We have been able to generate an increasing amount of data thanks to the advancements in technology, which have even reached a point where it is no longer manageable with the tools that are currently accessible. The phrase "big data" was coined as a result of this phenomenon to refer to data that is both comprehensive and difficult to manage. We must devise new methods for organizing this data and obtaining knowledge that is meaningful to achieve our current and future social needs. Among these unique societal needs is the provision of medical care. Healthcare organizations, just like businesses in every other sector, are collecting data at an incredible rate, which brings with it a plethora of opportunities as well as obstacles. With an emphasis on healthcare, this paper explores the basics of big data, including how it is administered and analyzed, and what future implications it may have.

Plant dependability key performance indicators have been an area that has become a focal point for initiatives in the current competitive market, where businesses all over the world are tightening their financial belts to reduce costs while simultaneously ensuring good service quality and safety [1]. Recently, businesses have come to the realization that their competitiveness, performance, and consequently their future are inextricably related to the successful and efficient management of maintenance [2, 3]. As a result, one's perception of maintenance undergoes a significant shift, shifting from that of a "necessary evil" to that of an "investment opportunity" that warrants optimization. The key to achieving excellence in maintenance is making the logical choice that balances costs and industrial performance [4]. Repairing and updating medical devices has become more complicated and costly during the last several years. This is because there has been a consistent rise in the number, variety, complexity, and expense of medical equipment.

Reference [5,6] Medical devices (MD) are regularly implicated in patient accidents, which can result in either death or injury, in addition to the costs associated with their upkeep. Healthcare organizations and clinical engineering are therefore subject to a legal requirement to ensure that their medical devices are of a high degree of safety and dependability, as well as to check the effectiveness of their maintenance methods. Specifically, we focus on applied and verified models in the healthcare domain, and we address a significant portion of the existing works on preventative maintenance optimization in this study. The purpose of this study is to examine several significant feature modeling equipment maintenance, analyze several research deficiencies that have been discovered in the literature on healthcare maintenance optimization modeling, and make suggestions for the development of appropriate tools for improved medical device management.

2. Literature Review

2.1. Healthcare Scheduling and Resource Optimization

This section aims to summarize the research on mathematical modeling's use in healthcare by providing a rundown of relevant studies. Numerous researchers have painstakingly investigated this subject, adding to the growing body of work connected to it. The following review of the literature will detail the most noteworthy findings and advancements in mathematical models used in healthcare.

There are a lot of mathematical models that have been used to solve complex optimization problems in healthcare. These models include dynamic programming, integer programming, stochastic programming, queuing theory, game theory, system dynamics, agent-based models, and linear programming (LP), multiple iteration linear programming (MILP), and stochastic programming. Files should be in MS Word format only and should be formatted for direct printing.

2.2. Artificial intelligence (AI) in the healthcare supply chain (HSC)

Supply chain management is just one of many industrial domains that might be radically altered by the introduction of AI [7,8]. Several areas of supply chain management have been found to benefit from the use of artificial intelligence. These include demand forecasting, facility location, supplier selection, supply chain risk management, inventory replenishment, and sustainability in supply chain functions. Most studies on AI in the supply chain have focused on generalized scenarios rather than particular industries, thus any useful insights may have been lost in translation. Furthermore, there is room for new research avenues since the current literature pays inadequate attention to the application of AI in HSCs.

A recent study predicted that the worldwide market for artificial intelligence would increase from 2017 to 2025 at a CAGR (compound annual growth rate) of 57%. The healthcare supply chain is just one of many areas where academic writings have recently focused on the possibilities presented by artificial intelligence [11]. The medical field is making extensive use of AI for both research and therapeutic purposes. Chronic disease management and drug discovery are two examples of these uses. Application of AI-based HSC within the framework of human-centered computing has the potential to enhance product delivery, tracking, inventory sharing, and resource pooling across stakeholders [12].

Authenticating medical gadgets, tracking down counterfeit products, and validating the validity of products are all possible with its assistance [13]. There have also been studies that have explored the enormous potential of artificial intelligence in terms of checking and establishing the pricing eligibility of manufacturers and enhancing healthcare data management [14]. In a recent study, the authors explored the possible uses of medical technology improved with artificial intelligence in HSCs [15].

Artificial intelligence (AI) based HSC offers a realistic solution to the current problems plaguing the HSC industry. The HSC arrangement achieves this by integrating several procurements, clinical, and financial management systems. According to [16], artificial intelligence can improve operational efficiency and patient quality, leading to a surplus in the healthcare industry's supply chain. Despite a wealth of data pointing to AI's potential positive effects on building a strong supply chain, no research has yet identified the most important variables for AI to be effective in the healthcare sector. A comprehensive examination of CSFs would bring an improvement in the quality of healthcare services, in addition to making the application of AI easier.

3. Methodology

3.1. The data overload

An enormous quantity of data is produced every day by individuals who are employed by a variety of firms located all around the world. In a single year, such enormous volumes of data are created, replicated, and consumed, and the term "digital universe" uses a quantitative definition to describe this phenomenon. In 2005, the digital universe was estimated to be around 130 exabytes (EB) in size by the International Data Corporation (IDC).

In the year 2017, the digital universe reached around 16,000 EB, which is equivalent to 16 zettabytes (ZB). By 2020, the digital universe will have expanded to 40,000 EB, according to industry research firm IDC. To put this enormity in context, it would be necessary to allocate around 5200 GB of data to every single person.

3.2. Healthcare as a big-data repository

Healthcare is a general term for a complex system whose principal goal is to protect people from harm by identifying and addressing health issues as they arise. Healthcare systems rely on a number of interdependent parts, the most crucial of which are the people who work in the medical field (doctors, nurses, etc.), the places where patients can get treatment (clinics, hospitals, etc.), the technology used for diagnosis and treatment, and the financial institutions that back these parts. Dentists, doctors, midwives, nurses, psychologists, physiotherapists, and a plethora of other professions make up the health experts.

3.3. Assurance of data quality

In order to ensure that the data contained in the register are of high quality and to protect against a variety of errors, it is necessary to establish structures, processes, policies, and procedures. These things include the following:

- Errors in interpretation or coding: This sort of mistake occurs, for instance, when two abstractors look for identical data elements in a patient's medical record but get different results from the same chart. This error might have been committed by abstractors. Variations in the categorization of specific situations or procedures also fall under the umbrella of interpretation mistakes. Methods that help find or prevent interpretation mistakes include re-abstraction, testing against standard charts, training on definitions accurately, and testing and reporting on inter-rater reliability.

3.4. Quality assurance

To determine whether a registry is useful for decision-making, it is necessary to have a firm understanding of the quality of the approaches that were utilized to gather the data, as well as the quality of the data that is recorded in the database. This is necessary. To determine whether or not the data contained within the registry is suitable for use in decision-making, it is necessary to have an understanding of the quality of the data contained within the registry. This is because patient registries that satisfy sufficient quality criteria (which are discussed in Chapters 1 and 25) are increasingly being seen as important means to generate evidence regarding the effectiveness, safety, and quality of care offered to patients. In addition to considering how to construct quality assurance methods that are suitable for their registries, registry planners should also consider how to ensure quality to a level that is sufficient for the objectives that are planned (as will be discussed further down in this entry). To review and report on the quality assurance activities is the obligation of the personnel who are in charge of the registry.

Depending on the function that the register is intended to fulfill, the quality assurance procedures that are utilized will vary accordingly. If a registry is intended to act as essential evidence for decisionmaking19 (for example, coverage determinations, product safety evaluations, or performance-based payment), then it will require higher levels of quality assurance than a registry that merely provides the natural history of a disease. This is because the natural history of a disease is the only thing that is described in a register. Quality assurance operations can be broken down into three basic categories: (1) quality assurance of data, (2) quality assurance of registry procedures, and (3) quality assurance of computerized systems. In general, these are the activities that are regarded to be responsible for quality assurance. There is a possibility that the amount of quality assurance that may be obtained may be limited owing to budgetary constraints. This is because many registries are fairly large.

It is strongly advised that a risk-based approach to quality assurance be utilized to strike a balance between the requirement for adequate quality assurance and the investment of reasonable resources intended for a specific purpose. A risk-based strategy concentrates on the most significant causes of errors or procedural breaches from the point of view of the registry's primary objective. During the phases of conception and design, it is important to identify potential sources of error. According to the information that will be presented below, registries that serve diverse objectives may be susceptible to a variety of error causes and may concentrate on a variety of procedures and levels of evaluation. In the future, if the results of different registries are going to be integrated or compared with one another, it is expected that the standardization of procedures for specific goals, such as national performance measurement, will become more widespread.

3.5. Mobile computing and mobile health(mHealth)

Through the utilization of the built-in pedometers of their portable and wearable devices, such as smartphones, smartwatches, fitness dashboards, or tablets, it seems that every single individual in the digital world of today is intrigued with tracking their fitness and health data.

This is especially true in the context of the digital world. The architecture of the healthcare system needs to be redesigned to support mobile devices. This is because modern society is becoming increasingly mobile in nearly every element of life. Mobile health, or mHealth, refers to the use of mobile devices in public and medical health and medical practice. This is standard procedure across the board in healthcare, especially for long-term conditions like cancer and diabetes. A growing number of healthcare companies are embracing mobile health and wellness services to bring new ideas to patient care and wellness coordination.

Through the acceleration of interactive contact between patients and healthcare practitioners, mobile platforms have the potential to greatly enhance healthcare. Research apps for health and fitness statistics can be developed on dedicated platforms like Google Fit and Apple's Research Kit. These apps provide seamless interaction with a wide range of consumer gadgets and embedded sensors, paving the way for data integration.

Medical providers can access all of your health records instantly with the help of these applications. In this way, users and their doctors can access real-time data regarding the user's health. In addition to assisting with wellness planning, these apps and smart devices also promote healthy habits. Users and patients alike can take an active role in protecting their health.

3.6. Nature of big data in healthcare

Electronic health records (EHRs) can provide a mountain of data, which could pave the way for better analytics and better clinical decision-making. On the flip side, a large chunk of this material is no longer structured. An example of "unstructured data" would be information that does not follow a preexisting model or structure. Maybe we can capture it in so many different forms, and that's why we've decided to do this. Another good reason to utilize an unstructured format is because structured input options (such as checkboxes, radio buttons, and drop-down menus) often don't do a good job of capturing complex data. For example, any other format would not allow us to document non-standard information related to a patient's socioeconomic status, preferences, vital lifestyle traits, clinical suspicions, and other patient-related details.

It is challenging to organize such a wide variety of sources of information, which continue to be essential, into a data format that is either intuitive or unified for further analysis utilizing algorithms to comprehend and make use of patient care. Despite this, the healthcare business is obligated to make full use of the potential offered by these abundant streams of information to improve the overall experience of individual patients. It has the potential to actualize in the field of healthcare in the form of improved management, care, and therapies that are more affordable. We have a long way to go before we successfully harness the insights that emerge from big data and realize the benefits that big data has to offer in a meaningful way. To achieve these goals, we must proceed with caution when dealing with and analyzing the massive amounts of data.

3.7. Management and analysis of big data

The term "big data" describes the rapid accumulation of large volumes of diverse data. Data collected from many sources is mainly needed to optimize consumer services, not for customer consumption optimization. Also, this is valid for massive datasets used in healthcare and biomedical studies. How to handle such a massive quantity of data is the biggest challenge that big data poses. For an analysis to be effective, the data has to be saved in a manner that is both easily accessible and comprehensible. The data cannot be made available to the scientific community without this. Using cutting-edge computer software, protocols, and hardware in healthcare facilities is one of the biggest obstacles when dealing with healthcare data. Working together with experts from several disciplines, including biology, IT, statistics, and mathematics, is crucial for achieving this goal. Cloud storage platforms with analytical tool developers' pre-installed software solutions make it possible to make the data collected by the sensors publicly available. Data mining and machine learning capabilities developed by AI experts would be a part of these technologies, allowing them to turn data into knowledge. After its implementation, it would make healthcare data acquisition, storage, analysis, and visualization more efficient. If we want to understand the problems better, we need this sophisticated data annotated, integrated, and presented acceptably.

In the absence of such pertinent information, the statistics pertaining to healthcare continue to be fairly hazy, and it is possible that biomedical researchers will not be able to proceed any further. When it comes to effectively displaying this freshly acquired information, visualization tools that were developed by computer graphics designers are finally available. Another difficulty that arises in the study of huge data is the heterogeneity of the data. Big data in healthcare is significantly less informative when using existing technologies because of its massive size and extremely heterogeneous character. Running the software framework that aids in the analysis of big data is most commonly done on high-power computer clusters that are accessible through grid computing infrastructures.

Cloud computing is one example of a system that uses virtualized storage technologies and provides reliable services. High degrees of autonomy, scalability, and stability are further benefits, along with comprehensive access, dynamic resource discovery, and composability. The ubiquitous sensors can provide data to these platforms, which can then analyze and interpreted it. The platform can also give user-friendly web visualizations. Mobile edge computing cloudlets and fog computing allow the Internet of Things to bring processing and analysis of big data closer to the data source. To apply machine learning and artificial intelligence strategies for big data analysis on computing clusters, advanced algorithms are necessary. For the purpose of writing such algorithms or software, a programming language that is ideal for working with large amounts of data, such as Python, R, or another language, could be utilized.

4. Results and discussions

The target values of 844.0 and 539.0, which were obtained during the two optimization methods, represent the overall quality of the solutions that are desired for both processes (see Table 1). In the first optimization phase, five possible solutions were identified based on the solution counts; however, in the subsequent procedure, only three solution counts were achieved. It appears that the most effective solutions contained the objective function values that were ideal. The optimal values achieved for the aim were 844.0 and 539.0. There is no significant difference between the best solutions and the theoretical lower bounds of the objective function, as shown by the best-bound values of 844.0 and 539.0. Since there is now no space for improvement, the fact that the gap values between the two methods are zero percent shows that the optimal solutions have been found. From these results, we can infer that the optimization algorithms found optimal solutions that minimize the goal function while satisfying all restrictions.

Table 1: Optimization results for the two model procedures

First Output		**Second Output**	
Term	**Value**	**Term**	**Value**
Objective value	844.0	Objective value	539.0
Solution count	5	Solution count	3
Best objective	844.0	Best objective	539.0
Best bound	844.0	Best bound	539.0
Gap	0.0%	Gap	0.0%

By emphasizing their relevance and model implications, the findings are thoroughly examined to show that the registry is successfully lowering the risk of agranulocytosis linked to clozapine use by acting as a warning mechanism. The sponsor can control who gets their hands on clozapine by making sure that only patients who qualify must provide their test data at certain intervals. Sponsors can also monitor patient populations for adverse effects, identify low counts, and avoid improper rechallenge (or re-exposure) in at-risk individuals. By using this approach, the sponsor can track the occurrence and severity of adverse events and make sure that the medication is only given to the right patients. The intricate interplay between molecular and physical events is exhibited by biological systems, such as human cells. To better understand the interdependencies of these complex systems, it is common practice in biomedical and biological investigations to gather data on a smaller and/or simpler component. Hence, a large-scale map of a particular biological phenomenon can only be achieved by doing a large number of reduced experiments. The biological mechanisms are becoming more apparent as our knowledge grows. Modern tools and techniques owe a great deal to this idea. Case in point: consider the mountain of data generated since human genes were deciphered using next-generation sequencing (NGS) and genome-wide association studies (GWAS). The use of next-generation sequencing (NGS) data adds a new dimension to the experimental setting by providing information at previously unattainable depths. It has allowed us to better monitor and record biological events linked to certain diseases in real-time, with a higher degree of precision. A wealth of information that is frequently overlooked or concealed in smaller experimental procedures may be uncovered by enormous amounts of data, which led to the emergence of the 'omics' era.Recent developments in the field of omics have allowed scientists to investigate an organism's entire genome in a very short period, rather than just one gene. Research in the field of "transcriptomics" has similarly expanded our ability to investigate gene expression beyond that of individual genes to encompass the whole "transcriptome" of a given organism. Massive amounts of data with unprecedented levels of detail are produced by each of these separate trials. But this level of detail and clarity may not be enough to explain a specific mechanism or occurrence. Consequently, it is not uncommon to have to go through mounds of data obtained from multiple experiments to find fresh insights. A growing body of literature addressing healthcare big data lends credence to this claim (Fig. 1). Big data analysis in the healthcare and medical systems can significantly help with the development of innovative healthcare solutions. Thanks to recent technological advancements in data gathering, collection, and analysis, there is hope for a personalized medicine revolution eventually.

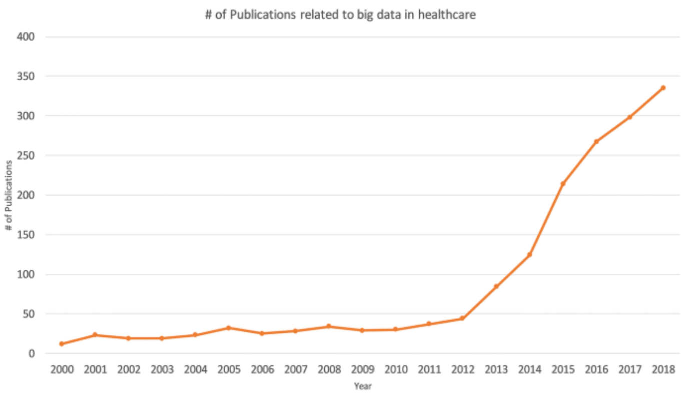

Figure 1: Big data in healthcare

Table 2: Optimization results for first and second outputs

Term	First Output	Second Output	Description
Objective Value	844.0	539.0	Optimized value of the objective function. Represents key measures like total cost or profit.
Solution Count	5	3	Number of feasible solutions satisfying all constraints.
Best Objective, Bound	844.0	539.0	Best value and lowest value found for the function during optimization.
Gap	0.0%	0.0%	Difference between best bound and best objective.
Staff Assignments	20	30	Allocation of staff members to specific time slots for effective scheduling.
Patient Assignments	30	20	Allocation of patients to specific time slots for ensuring timely care.
Resource Allocations	10	15	Allocation of resources to specific time slots for effective resource management.
Staff Overtime Hours	10	7	Extra hours required by staff beyond regular hours for monitoring workload distribution.

Extensive definitions of the words used in the optimization techniques are provided in Table 2. The results are thoroughly examined by emphasizing their relevance and the ramifications for the model.

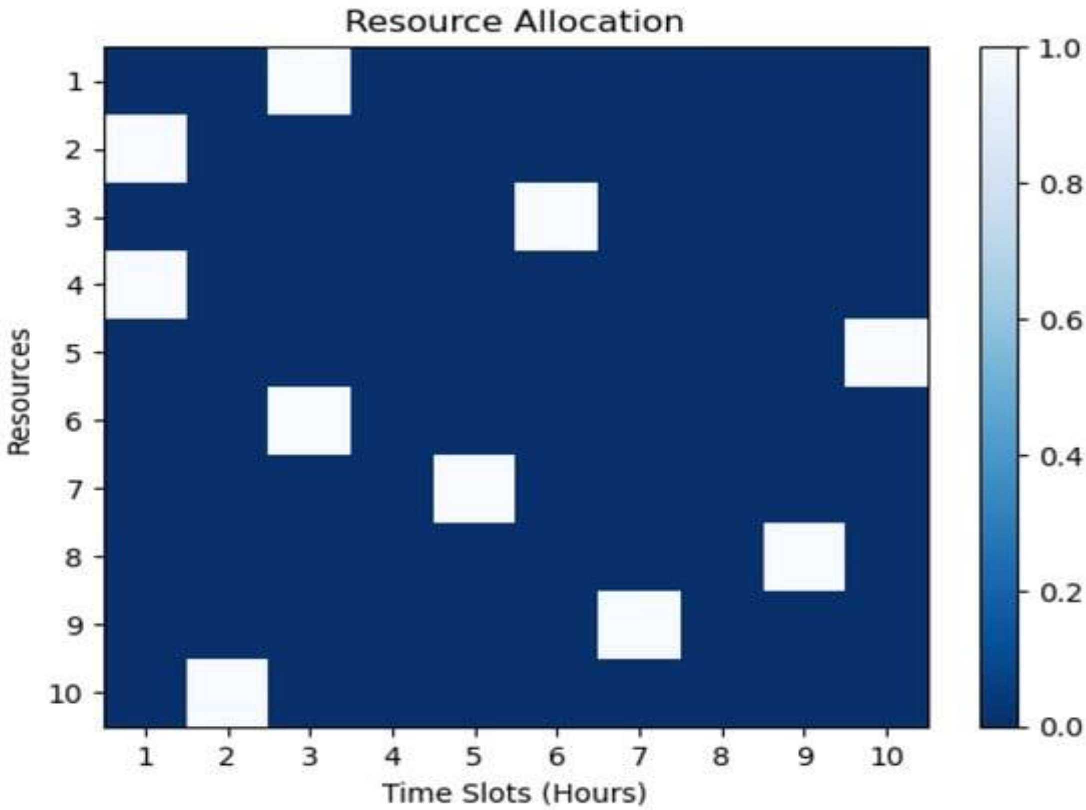

Figure 2: Visual representation of the first model procedure's resource allocation

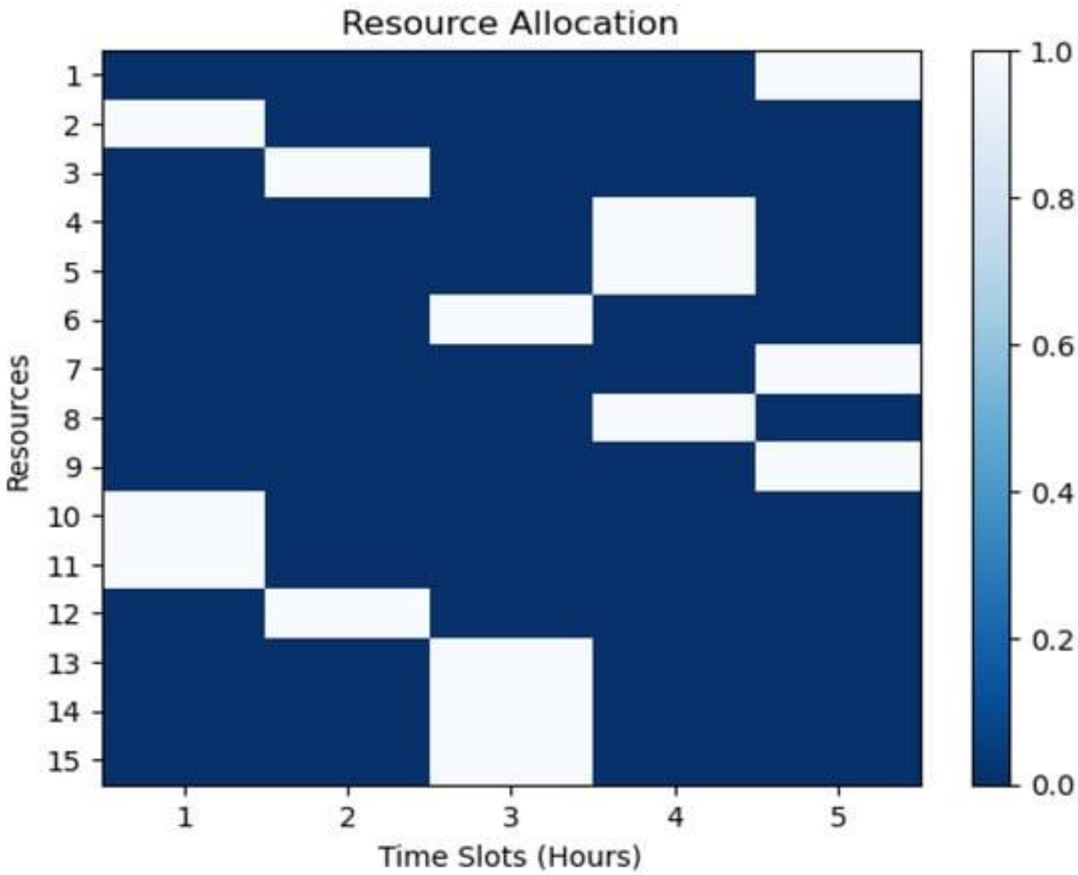

Figure 3: Heatmap depicting the distribution of resources during the second model process

Medical schedule optimization research shows, in Figures 3 and 4, how resources are split between the two model operations' time slots. While optimizing, the visualizations show the amounts of resources used and those that are still available.

5. Conclusion

Genomics, mobile biometric sensors, and healthcare applications on smartphones are just a few examples of the modern biomedical and healthcare technologies that produce massive amounts of data. Therefore, we must understand what this data can do and evaluate its potential. Healthcare, for instance, can benefit from additional insights gained from analyzing such data in terms of technical, medical, procedural, and other forms of improvement. Reviewing these medical procedures, it seems that tailored medicine, which focuses on each patient, is reaching its full potential. Data from electronic health records (EHRs), medical records (EMRs), and other sources is being used to improve prognoses through big data analysis. Healthcare analytics and clinical transformation service providers are helping to improve and improve patient outcomes. To combat big data fraud, improve treatment method platforms, reduce analytics costs, and develop efficient Clinical Decision Support (CDS) systems, all of these companies have made a commitment. One federal concern that almost all of them face is the handling, sharing, and security of private data. When healthcare organizations and biological researchers pool their data, it improves disease prognosis, diagnosis, and therapy. This has also helped strengthen the system of personalized healthcare, making it more health-oriented and resilient. The contemporary healthcare community has embraced big data analytics into clinical procedures and healthcare systems as a whole after seeing the possibilities presented by big data. Finding actionable insights in enormous datasets is now much easier, thanks to the rise of supercomputers and quantum computers. Researchers are rushing into biomedical big data despite infrastructure difficulties in the hopes of finding new and useful insights that will enhance healthcare services. Clinical trials, merging insurance and pharmaceutical claims, and finding biomarkers are all examples of creative and novel ways to analyze healthcare big data.

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