An-Najah National University

Faculty of Graduate Studies

DEVELOPMENT OF A MATHEMATICAL MODEL FOR OPTIMAL SCHEDULING OF PATIENTS AND RESOURCE MANAGEMENT IN HEALTHCARE IN PALESTINE DURING THE PANDEMIC

By

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Dedication

(وَلَسَوْفَ يُعْطِيكَ رَبُّكَ فَتَرْضَى)

I dedicate this project to God my source of inspiration, wisdom, knowledge and understanding.

To my beloved mother the most affectionate person in the world, who is encouraging and helping me to fight hard to makes my dreams come true. Mom thank you for being a constant source of support during life and through the process of pursuing the master degree. I am truly thankful for having you in my life.

To my lovely father, the source of power and support who raised me until I became what I am today.

To my family and friends for their everlasting support and help.

I dedicate my thesis with big love.

Lana

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Finally, I gratefully acknowledge all who, directly or indirectly helped me to complete my thesis successfully.

Declaration

I, the undersigned, declare that I submitted the thesis entitled:

DEVELOPMENT OF A MATHEMATICAL MODEL FOR OPTIMAL SCHEDULING OF PATIENTS AND RESOURCE MANAGEMENT IN HEALTHCARE IN PALESTINE DURING THE PANDEMIC

I declare that the work provided in this thesis, unless otherwise referenced, is the researcher's own work, and has not been submitted elsewhere for any other degree or qualification.

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Signature: Lana Ghannam

Date: 27/1/2022

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Abstract

The resource planning for hospitals has attained a huge attention by researchers in the last few decades, but the effect of human aspects in design and managing it has been ignored. In this research, we integrate physicians' differences to examine their effect on patient waiting time and so on patient satisfaction. More specifically, a more realistic mixed integer linear programming model is proposed to deal efficiently with determining the maximum number of patients living with different types of clinical complications and is likely to contribute to determining the requirement of physicians and making arrangement for them. Considering different levels of physicians and different types of departments, the model aims to facilitate the health-care organizations in analyzing their physicians for delivering high-quality care services. In addition, it aims to derive an assignment between immunity, skills, and the experience as well as an optimal selection of physicians. A non-dominated sorting genetic algorithm II (NSGS-II) is conducted to confirm the verification of the proposed model and carries out human resource planning in hospitals on the basis of these factors. The results of conducting sensitivity analysis demonstrated that, after considering classification of patients and physicians' issues cause a significant improvement in the efficiency of hospitals in the future. Moreover, the number of physicians for each department varies with different patient types, so the allocation of medical specialists across the hospital requires information regarding demands, such as the classification of patients, and the rates of morbidity within the health-care sector. The health-care organizations associated with

the public domain require efficient allocation of the clinical specialist. Also, the assignments vary with different physicians' classifications.

Chapter One
Introduction and Theoretical Background

1.1 General Background

World leaders in what is called "Global Development" are looking forward "end poverty; promote prosperity and people's well-being while protecting the environment by 2030" (Carter et al., 2018). The third goal of sustainable development aims to ensure that all individuals in the world of all ages enjoy good health and the necessary health care (Lönnroth and Raviglione, 2015). Besides, many laws, legislations, and international institutions such as the world health organization (WHO) that control the work and quality of the healthcare sector put a great effort into this area (Levy and Morrison, 2009). Therefore, all countries should pay attention to their health care sector and provide the necessary capabilities to develop this sector (Adashi et al., 2010). Institutions that work in the healthcare sector, whether governmental or private, are concerned with providing high-quality health care (Browne et al., 2012).

While maintaining superior quality of patient service, many hospital quality and hospital services measures are created using the concept of hospital resource planning, which has grown up with the spread of epidemics greatly throughout the ages (Green, 2006). It is necessary to have a clear resource plan in every organization or company in any sector (Richard et al., 2015). Implementing a good resource planning process helps the organization to maintain its success and sustainability (Sugumaran and Dekkers, 2014). Resource management denotes a type of management that is concerned with setting objectives, developing the vision, formulating and implementing strategies and plans and correcting the deviations (Nyaoga et al., 2015). One of the most important factors that guarantees the success and development of resource planning is to adopt a strong supply chain management (SCM) that enables it to provide the best within the available resources (Shen and Li, 2010). Accordingly, it can be affirmed that organizations are exposed to threats to their supply chain because of multiple drivers including economic competitiveness, demand uncertainty, challenging market environment, and increased globalization (Ansari and Kant, 2017). SCM is considered as one of the significant sources of higher competitive advantages because its most significant goal is to develop capabilities of the business firms that can help them in outperforming their rivals (World Economic Forum, 2019). Therefore, improvement in SCM processes is likely to improve inventory management, manufacturing, and transportation and satisfying customers' needs, while improving the overall operations management (OM) of the business (Pirim et al., 2014). Although we cannot sometimes prevent long and combined outbreaks from occurring, a well-thought-out SCM and process optimization can greatly mitigate the effects of a crisis (Koech et al., 2014). Varying nature and type of the crises in the healthcare sector, prevailing pandemic conditions, and hospitals' network have created challenges for Supply Chain Management in Health Care (SCMHC) (de Vries and Huijsman, 2011).

When an epidemic spreads, it spreads due to the lack of control, preparing for that situation falls under the hands of human technological advancement, how they can manage it, what prevention action we can take (WHO Europe, 2009). Weak preparation for future potential pandemic leads to the rapid spread of disease, and so on increasing service demands that could potentially overwhelm hospital capacity and the health care system in general (World, 2020). Getting out of crisis and pressure that may lead to the depletion of resources and may even lead to failure to implement tasks in an emergency, need an emergency plan that should cover the maximum in the most difficult circumstances (Levin et al., 2007). However, hospitals have to face numerous barriers during the implementing of the SCM system. These barriers are less SCM in health care sector experience, lack of expertise, fewer technical and financial resources and less accurate data (Ledlow et al., 2016). It is a fact that the key factors associated with adopting SCM in hospitals are not only reducing the cost, caused due to their medical devices and services, but also are to stand in front of global epidemics that destroyed the economy of many countries (McKibbin and Fernando, 2020).

1.2 Problem Statement

In the present crises of (COVID-19), it becomes clear that there is a flaw in the resource planning of the Palestine Ministry of Health (PMOH). Resource planning of the PMOH failed to develop a detailed plan to provide it's caring for and treating patients in parallel with planning for the crises including expanding available physician's capacity during the COVID-19 pandemic (AlKhaldi et al., 2020).

Patients come to the hospitals with different diseases (COVID, Flu, fractures, etc.) require different physicians per period, for example COVID patient’s attention requires physicians with high immunity, skills and experience compared with a regular patient. Patients with infectious diseases like COVID should not stay in the same room as non-infectious unless there’s no infection risk associated with it. It is also important to consider the maximum number of days a patient is allowed to wait, otherwise it is considered as not satisfied, and patients are classified into COVID and non- COVID. According to Lei and Palm (2020), the strategies utilized by the health-care management to treat patients with different classifications without experiencing human resource limitations and physicians’ classification, and diagnostic ambiguity is only possible after assuring that the resources are efficient enough for delivering care services to the patients with full capacity. In the context of scheduling, Güler and Geçici (2020) argued that to integrate human resources scheduling system in hospitals, we need to focus on other factors like physician behavior. The current study's primary goal is to reduce patient waiting time and infection risk during a pandemic. Low physician’s immunity, skills, experiences are believed to be one of the important factors of increasing patients waiting time and infection in hospital caused by the treatment activities. Thus, selecting and allocating physicians based on these characteristics will reduce patient waiting time and infection risk. Hospitals, on the other hand, can enhance their human resource performance and boost patient satisfaction by incorporating physicians' experiences, skills, and immunities in scheduling. The model proposed in this study would overcome the limitations of previous models by incorporating physicians' immunity, skills, and experience, as well as certain other variants, and it would allow hospitals to efficiently assign physicians to treat the given patients while also studying the effect on patient waiting time and thus patient satisfaction.

1.3 Significance of Research

The significance of this research derives from the importance of integrating the physicians’ differences (i.e., immunity, skills, and experience) and managing the selection, and assigning of physicians in the hospital. This research aims to study the effect of this integration on giving high-quality care services in hospitals by improving their human resource capacity for delivering care services during the pandemic situation.

1.4 Research Questions

This study aims to answer the following questions:

- How can selecting physicians by their differences affect optimizing human resource planning process by allocating hospitals' physicians' during pandemic?
- How can selecting physicians by their differences affect the patient's waiting time and patient satisfaction?

1.5 Research Goal

Built upon the key benefits and values of hospital human resource planning implementation that circulate in the related literature, the ultimate purpose of this research is to improve PMOH's performance during COVID-19 pandemic to strengthen the ability of health facilities during the pandemic, or any other emergency or disaster, so hospital administrators can make sure that general priority action is taken and then give recommendations for future directions in PMOH's plans and strategy. Accordingly, the research objectives are:

- Integrating physicians' preferences in optimizing human resource planning process by allocating hospitals' physicians with the flow of patient's type during a pandemic, and other uncertain situations.
- Developing a mathematical model that helps policy-makers manage the relation between physicians' and minimize the waiting time for the patient and hence increase patient satisfaction in the healthcare settings.

1.6 Research Methodology

The research will be started by defining the problem. An extensive review of related literature is presented in a way to formulate the basis of the proposed study. Then, a mixed integer linear model (MILP) will be developed by selecting the parameters, variables, constraints and the objective functions. In addition, the data required to test the developed model will be collected from the related literature. The model will be tested and validated by conducting sensitivity analysis to test the robustness of the results of the model. The model can be tested using a given set of conditions and the results of these tests can be examined based on reality to validate the model (Mirzaeifar and Elahinia, 2015). The MILP model is utilized for system analysis, as well as optimization, and presenting flexible and powerful method to solve large, and complex problems and the situations requiring process integration (Kantor et al., 2020) due to a range of advantages since this system has been widely utilized within the healthcare systems.

1.7 Thesis Organization

This thesis is organized as follows: Chapter one reviews the literature related to human resource planning in hospitals, human resource planning during pandemic, Physicians Admission Scheduling Problem (PASP), framework for human resource planning in hospitals including patients, physicians and their behavior including immunity, skills, experience and their effect on human resource efficiency and patient satisfaction. This chapter discusses the concepts of lead time, process and tasks, non-human resources, and the hospital in Palestine during pandemic. Chapter Two presents the mathematical description and formulation of the proposed model. The model is presented with its assumptions, sets, parameters, objective function components, and constraints. Chapter three presents the numerical study and the computational results. The results include the workforce plan for physicians (i.e., the physicians needed, physicians' classifications, and shifts), the physicians to be selected, the assignment of physicians and departments, and the number of physicians needed for each department. Chapter four discusses the results of conducting sensitivity analysis. In addition, conclusions and limitations of the proposed model are presented.

1.8 Supply Chain Management

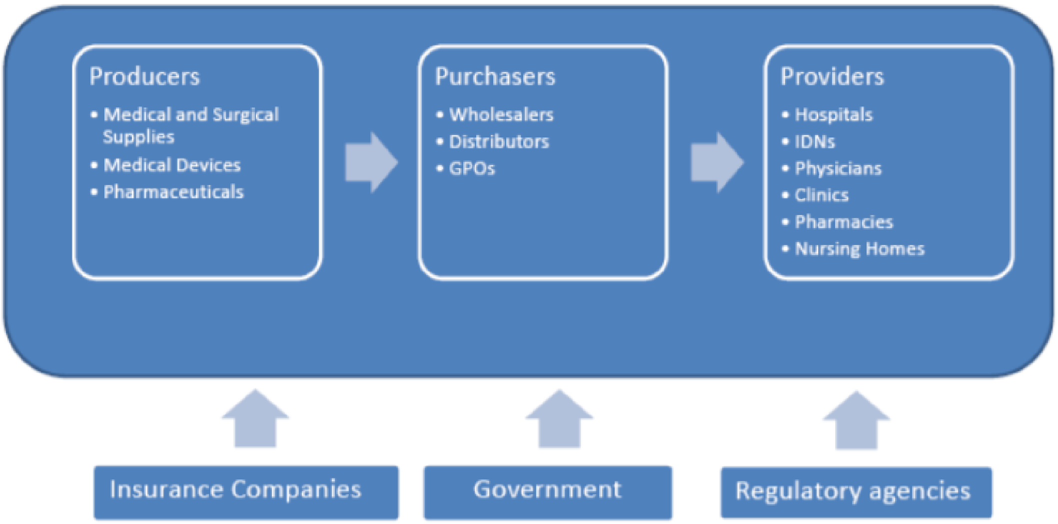
The area of SCM has gained the attention of various practitioners and researchers globally (Pandey, 2001). SCM has been defined by various researchers differently (Felea and Albăstroiu, 2013). One of the commonly cited definitions of SCM is presented by Mentzer et al. (2008). They defined SCM as the systemic and strategic coordination with business functions within a company by analyzing processes and resources, to improve performance for the company as a whole (Mentzer et al., 2008). SCM was defined as "an integrating philosophy to manage the total flow of a distribution channel from supplier to the ultimate customer" (Cooper et al., 1997). Lambert and Cooper (2000) added that the complete chain of distributors, warehouses, manufacturers, retailers, suppliers, business customers, end consumers, and even the suppliers of suppliers is considered in the supply chain (Lambert & Cooper, 2000). The ultimate goal of the efficient supply chain is targeted towards minimizing the different types of costs such as inventory costs, manufacturing costs, and transportation costs along with taking care of customer satisfaction (Carter and Rogers, 2008). The three basic objectives of SCM are reducing the cycle time, getting/delivering the right product to the right place, and keeping different types of costs as low as possible while maintaining superior quality of customer service (Gold et al., 2010). Different demand-supply chain models have been used by firms using these techniques to optimize their supply chain (Tynjälä, 2011). Organizations study and analyze their capacity and operations management (OM) by taking different methodologies, frameworks, and techniques to evaluate results (Nolte and Nolte, 2008). Optimizing the supply chain can be performed by reducing the cycle time and delivering the right product to the customers at the right time (Zijm et al., 2019). Achieving strategic fit between the demand and supply capabilities of the business requires carrying out subsequent changes in SCM operations (Stolze et al., 2016).

1.8.1 Supply Chain in the Health-Care

According to Mathew et al. (2013), the supply chain in the health-care industry has a complex nature, and it is challenging to remove the inefficiencies and drive down the cost of care. The supply chain of health-care includes the flow of different types of products, and requires the participation of different stakeholders. The main purpose of the supply chain of health-care is the delivery of products in a timely manner for fulfilling the needs of the stakeholders (Mathew et al., 2013). On the basis of their functions, the stakeholders in the health-care supply chains are categorized into three major groups, including producers, purchasers, along with the providers. Figure 1 depicts the stakeholders of health-care supply chains.

Figure 1

Configuration of Healthcare supply Chain (Source: Mathew, John, and Kumar, 2013)



The research conducted by Paul and Venkateswaran (2020) proclaimed that the supply chain operations of the health-care sector have a significant influence on the strategies carried out for controlling the epidemic outbreak. The provision of adequate flow of medicaments along with other products for avoiding the shortage of materials. Govindan et al. (2020) and Ivanov (2020) proclaimed that the supply chain operations are likely to have a significant influence on the duration of a pandemic. The SCM decision-makers are well-equipped for utilizing the available technologies, and techniques to predict the potential impacts of the pandemic on the human resource planning of their firms.

1.9 Human Resource Planning

1.9.1 Human Resource Planning in Hospitals

The implementation of the analytics techniques for supporting SCM in the logistics operations minimizes the impacts of the epidemic on the human resource planning. There are several definitions of the term human resource planning. Human resource planning process centered towards the claim that organizations can have a competitive advantage within their perspective industries if they own different crucial resources that include both tangible and intangible types of resources (Jonsson, 2016). It came under light after the emergence of research studies conducted by researchers such as Das and Teng (2000). They mentioned that the effective management of the firm's human resources both tangible and intangible human resources can result not only in elevating firm performance, but the firm can also outperform its competitors, and added that the firm's resources and assets can also help the firm in implementing such strategies that can eventually lead to achieving organizational short-term and long-term goals (Das and Teng, 2000). The interaction of market conditions and the firm's human resources helps in determining the value of firm's resources (Grant, 2009). However, firms cannot only gain maximized opportunities from the specific market but can also avoid fierce competition within the market by understanding the value of a firm's crucial resources (Madhani, 2009).

Hospitals have also been focusing on adopting human resource planning strategies (Al-Saa'da et al., 2013). Hospital human resource planning is essential in developing improved methods, policies, and decision-making tools to improve the overall performance of the SCM system (Bhattacharjee and Ray, 2014). Evans et al. (2017) extended human resource planning and SCM in their research by the inclusion of dynamic capabilities (Evans et al., 2017). The ability of SCM in bringing different adjustments such as the overall strategy development, integration, and human resource allocation towards crucial resources plan can be referred as dynamic capabilities of the organization (Agwunobi and Osborne, 2016). Furthermore, Sanja (2013) argued that the human resource planning can be found when the organization is involved in making different investments in the SCM system such as in technologies, systems, people, and processes (Sanja, 2013). Keeping in view both of these studies, it can be said that both investments and dynamic capabilities can be added to resource planning for the adoption of resource planning practices.

Human resource planning can help in achieving a competitive advantage for the healthcare sectors (Moe et al., 2007). Nevertheless, resource planning plays the role of a motivational factor in the way to adopt SCM practices in the health sector (Healthcare Sector Supply Chain Strategy Expert Panel, 2017). The proposed study will also be targeted towards finding the main factors of different hospital resources such as financial resources, technological capabilities, and informational resources on the adoption of hospital SCM practices. During the last decade, the literature on human resource planning has grown remarkably (Durrani, 2016). While many of recent research studies in the hospital have tried to explore the effects of physician's allocation on mortality rate as an indicator (Withanachchi et al., 2007). Studying one factor or indicator is not enough and had forced researchers to be involved in multi-factor by using Monte Carlo simulation models (Staiger et al., 2003). However, many of the researchers then discussed the patient allocation model with physician's allocation side by side (Sun et al., 2014). The reactiveness of the hospital towards resource planning is mainly related to an optimization approach (Carvalho et al., 2017). The Data Envelopment Analysis (DEA) model was used to optimize hospital performance by studying the overall efficiency of a given hospital (Caballer-Tarazona et al., 2010). The authors further added that studying the efficiency to optimize the use of the human resource is more accurate in each hospital's activity (World Health Organization., 2016).

According to spatial-allocation model for regional health-services planning, health center location model recognizes the negative effect of distance on utilization, since this method is centered towards the location and capacities of a specified number of health-care centers (Jun et al., 2010). Another study found that there is an interaction of unit capacity levels in a progressive patient care hospital and utilization levels, percent of transfers between department, and proportion of patient-days resulting from inappropriate use for each unit in the hospital make an impact of capacity level in one unit on the performance of other units (Drazen and Rhoads, 2011). In addition, some studies extended the factors by the inclusion of nonlinear programming, which studied the relationship between the number and type of patients, size, and location of facilities in minimizing facility costs and patient transportation (Boonmee et al., 2017). Torabipour et al. (2016) recommended that further study should understand more the variables related to this field such as physician's behavior. Stochastic models were used to assess the cost by adding value of the waiting time and converting this value to a prediction cost.

1.9.2 Human Resource Planning during the Pandemic

Understanding human resource planning is an integral component of pandemic planning (Toner and Waldhorn, 2006). The influenza pandemic model, which quantifies a pandemic's potential impact on the expected demand for medical care. The model is developed primarily to assess the possible increase in healthcare demand and forecast resource usage in the event of pandemic influenza (Zhang et al., 2006). Integrating resource plan and potential population rates as a pandemic model make FluSurge a valuable tool to evaluate health care pandemic preparedness. Nevertheless, FluSurge can only be used to model that demand in one specific facility as opposed to the network of facilities providing medical care to the population in a broader region, offering a detailed development of its predicted outcomes (Woodul et al., 2019). During the fall pandemic (H1N1) 2009, a primary period measure was midnight occupancy for non-H1N1 patients and H1N1 patients. Although lower thresholds have been suggested as the decline in quality and safety where a hospital has no human resource planning for allocating physician by the patient type (Sills et al., 2011).

According to Schoenmeyr et al. (2009), there is a positive impact of the percentage occupancy and waiting time to improve dealing with the pandemic in hospitals, claiming that the adoption of alternative physician-to-service policies and doctors configurations on patient type, the frequency with capacity expedience, and patient waiting time, has also a significant role to play in this regard (Schoenmeyr et al., 2009). Kokangul (2008) found that stochastic service times and physician movement between departments through the facility is the most important factors that provides an accurate approximation in the general case during pandemic. Many authors have suggested the use of scheduling to achieve optimal utilization during a pandemic. Methods such as determining the maximum number of admissions that can be booked each day to maximize average occupancy over the planning horizon (Bekker and Koeleman, 2011).

1.10 Scheduling the Shifts of Physicians during COVID-19 Pandemic

This section presents the physicians scheduling problem that is related to the assignment of physicians to the patients over a given time horizon for maximizing the efficiency of treatment and increasing the service quality of patients. Each physician needs to stay in the hospital for a period of time and shifts to give the required service. Therefore, scheduling physicians inside a hospital is a challenging task and requires significance knowledge and experience (Gunawan and Lau, 2013). A genetic algorithm to optimize long-term physicians scheduling strategies for balancing the competing objectives of efficiency, and fairness was introduced by Brunner and Edenharter (2011). Hidri et al. (2020) tend to manage the issue of physicians planning under stochastic demand requirements by using an integer linear programming model for optimizing the utilization of the physicians of the operating department with reference to the emergency admissions. Ceschia and Schaerf (2012) introduced a dynamic variant of accounting for the uncertain length of stay, delays in admission, as well as patient's classification. Despite their effectiveness, these models failed to address the patient type, uncertain patient flow, and several other factors.

Thus, an efficient planning and physicians scheduling model becomes increasingly important for the healthcare sector. Leerapan et al (2021) suggested that there is a requirement to implement the decision-making models for providing the estimates of the surpluses, as well as shortages of the physicians which might be required in case of outbreaks at different geographical locations. It is significant to understand the potential dynamics of physicians during the pandemic situation, including the potential consequences of physician's gaps in public health (Leerapan et al., 2021). The implementation of decision-making models is also likely to provide additional values to the preparedness plans and simulation exercises for delivering high-quality healthcare services to the population. For carrying out resource planning and physicians scheduling during the pandemic situation, the policy makers and advisors are required to have indications regarding the regional distribution of the human resources which are currently utilized within the healthcare system. The analysis of the appropriateness of physicians, the gaps in physicians, and potential impacts of the physician's gaps on public health during a pandemic is likely to facilitate in arranging more physicians for fulfilling the current demands of the healthcare. According to Ndeffo Mbah and Gilligan (2011), limited supply of the HR forces the decision-makers in determining the manner in which the current human resources are required to be deployed within the healthcare sector, and the strategies which are required to be implemented for prioritizing the resources. Güler and Geçici (2020) provided advancement to an already existing model of Mixed-Integer Programming (MIP) formulation. This advancement is proposed to particularly resolve the physician's scheduling problem in the hospitals by providing optimal solutions. The model is divided into two stages. The first model proposes a mathematical model that resolves the limitations associated with the previous models. Secondly, the study applies an exact method to attain an optimal solution to the physician's scheduling problem against the existing tactics during

COVID pandemic. The research contains many mathematical formulation units, each corresponding to a different variable involved in resolving physicians scheduling problem under hospital management such as allocation of the physicians, the properties of the departments, etc. Also, the proposed model is parameter-free. The significance of this model is high, stating that it does not require pre-processing of the violation penalties and can be implemented on all the restrictions that are found with the previous existing model. Nevertheless, the weaknesses of this mathematical model include handling larger instances and designing such techniques that enhance the MIP performance. Hence, this model has its stark limitations in pandemic and emergencies requiring allocating physicians by their behavior analysis including immunity, skills, experience, with uncertain patient flow.

To overcome the limitations pertaining to handling large number of patients with uncertain patient flow in pandemic and emergencies, Marchesi et al. (2020) proposed a two-stage stochastic programming model having fixed recourse for the managers at Emergency Departments (ED) of the hospitals. It would help them in scheduling and staffing the healthcare professionals and align them in the right manner as per the emergency demands. This model would determine the number of physicians required for each shift and the staffing level in the ED. The model includes a total of 20 parameters involving number of days in planning the horizon, shift duration, case probability, the workload for physicians on weekdays/weekends, total physician workload, staffing period, and thirteen other significant parameters. This model potentially assists in improving the alignment between the demand and emergency healthcare services that eventually lowers the risk of treatment delays. The primary weakness of this proposed model is that it involves an assumption of having a constant rate of patient services that is not practicable in most of the scenarios. Though it is a suitable assumption since the patients seeking urgent care are catered immediately without having to wait in line for prompt assessment. Yet, there are variations in the patient type as well as differences in the service time which are not addressed through this model.

Furthermore, Zucchi et al. (2020) proposed a Mixed Integer Linear Programming (MILP) formulation that helps the hospital management in personnel scheduling during COVID-19 pandemic. This model entails three primary parameters, including the minimum number of working hours per week, the maximum number of working hours per week. The last parameter is a binary parameter deciding whether the employee works in a sector or not. This model successively resolves a challenging problem of personnel scheduling faced by the Italian pharmaceutical distribution warehouse with the help of optimal solution. Hammouri and Alrifai (2014) discussed physicians scheduling problem to assess the biogeography-based optimization (BBO) while focusing on the soft and hard constraints. However, further research is needed as the outcomes with other meta-heuristic algorithms leading to imbalance within the exploitation and exploration capacity. Hammouri (2020) provided a modified BBO algorithm through guided department selecting criteria for Physicians Admission Scheduling Problem (PASP). Despite the claims as most suitable, the proposed approach reached a stagnant stage quite early during the initial research phase and hence demanded further investigation. Ceschia and Schaerf (2012) assessed physicians scheduling problem with respect to OR constraints, patient delays, and flexible horizons. Nonetheless, their findings revealed that physicians scheduling problem was not sufficient enough to carefully model the hospital lifecycle. Range et al. (2014) focused on new ways to resolve physicians scheduling problem issues. However, their proposed model was only successful for small instances to resolve physicians scheduling problem issues and was not efficient to solve critical challenges. Turhan and Bilgen (2016) analyzed an MIP-based heuristic for physicians scheduling problem. The proposed solution provided high-quality solutions within 3 minutes and were feasible for larger instances as well. However, the model did not take into account, physicians' availabilities, and physicians' behavior. Marchesi et al. (2020) studied stochastic programming for physicians scheduling problem. However, the model made use of constant assumed physician rates and classification throughout planning horizon which is not an ideal situation.

The above literature provides enough evidence regarding certain mathematical models involving particular model factors and variables. However, the research also finds research gap in the models. One of the significant gaps is related to the fact that it does not include enough number of model parameters to be used in any of the three models. For pandemics like COVID-19, it is most essential to involve adequate amount of model parameters such as patient type, immunity and skills and experience for the physicians, waiting time and patient satisfaction, etc. which would help in attaining the ideal outcome (Marin-Garcia et al., 2020). In addition, the right selection between physicians to patients also seems to be a big research gap.

Since this study focuses on the physician’s scheduling problem for hospitals during pandemic, analyzing the consequences of physicians scheduling problem within the healthcare organizations, various models have been previously implemented within the healthcare organizations. The Mixed-Integer Programming (MIP) was an efficient model proposed by Demeester et al. (2010), which facilitated physicians scheduling problem up to a certain extent; however, the model required pre-processing of the violation penalties, which was a significant limitation. The MIP model was further upgraded by Bastos et al. (2019), and included more mathematical formulation units such that each of unit corresponded to a different variable for physicians scheduling problem management, including the allocation of departments, the properties of the room, along with several other factors. However, this model was weak in handling large instances and was not suitable during situations, such as a pandemic, and emergencies requiring accommodation, administrations, as well as handling of the uncertain patient flow. To overcome this limitation, a two-stage stochastic programming model with fixed human resources for the managers was proposed by Güler and Geçici (2020) for providing facilitation in scheduling, staffing, and alignment of the healthcare professionals according to the emergency care demands. However, this model as based on the assumption that a different physician classification and behavior is not practical in certain scenarios.

Physician’s scheduling is strongly influenced by physicians, scheduling criteria, number of staff, along with certain other factors. Analyzing the significance of the implementation of physicians scheduling problem model within the healthcare organization, as well as the identification of limitations to the previous models, this research includes some of the variants, including physicians’ skills, experiences, immunity and the flow of physicians between department during a pandemic, and other uncertain situations. As an extension of previous models, the model proposed within this research would overcome the limitations of the physician classification models and incorporate their skills, experience, immunity and certain other variants and study the effect of this classification on decreasing waiting time for the patient and patient satisfaction accordingly.

1.11 Framework for Resource Planning in Hospitals

In recent years, many hospitals put efforts in adopting human resource planning practices. There have been growing interests of the researchers in examining the factors affecting the hospital firms in adopting the human resource planning strategies (Gupta and Ramesh, 2015). The increased attention towards human resource planning practices is due to increased awareness about the sensitivity of this issue both at health and government level (Duque-Uribe et al. 2019). Most factors found to be: patients, physicians' number, number and type of departments, immunity, skills and experience, lead time and waiting time, process and tasks.

1.11.1 Patients

Patient's type must be efficiently planned and managed (Mosadeghrad, 2014). Increased demand makes hospital patients planning difficult (Ben Bachouch et al., 2012). The average number of patients can be used as a measure for resource usage, which is the percentage of total number of patients used in a specific period (Munavalli et al., 2017). Hospital patients planning during pandemic like COVID should take into account three types of patients, COVID patients and non-COVID patients and patients in the emergency department with no classification yet. COVID patients are located to COVID department, while non-COVID patients are located to non-COVID department.

According to Munavalli et al. (2017), due to the local control of the operations and limited resources, the health-care organizations experience difficulty in handling uncertainty, and variability in demands. According to Ramirez et al. (2011), the health-care sector considers the potential care-related requirements of the patients, and most often allocate physicians for delivering care services to the patients based on their type. Ramirez et al. (2011) discussed that the model presented in the Dowson report emphasized on the integration of physicians for achieving for delivering appropriate care services to the service patients. However, the integrated human resource allocation was found to decrease the cost of care. For this reason, there is a requirement to emphasize on considering the needs of patients requiring care services, and allocating physicians to them accordingly.

According to Boyd et al. (2014), the patients planning is likely to create balance in the health-care supply and demands systems by implementing the measures to prevent incidents and preparing the systems for responding to the delivery of care services to the patients requiring health care. The patients planning frameworks implemented within the health-care organization is required to have structures, resources, processes, as well as governance, for the development, and implementation of suitable plans (Boyd et al., 2014).

1.11.1 Number and Type of Physicians

In achieving organization goals, human resource management plays a vital role (Nobakht et al., 2018). The quality of services provided in hospitals is closely linked with HRM (Gowen et al., 2006). Having adequate number of physicians in hospitals improves the quality of healthcare services through increased efficiency and labor utilization optimization (Part, 2010).

According to Cogin et al. (2016), the physicians planning adopted by the hospital improves the operational efficiency of the healthcare organization. In response to the major challenges which are likely to be experienced by the healthcare organizations, it is recommended to adopt commitment-based approaches and frameworks for human resources planning and management. On the other hand, Khatri et al. (2017) emphasized on implementation of the dynamic capability framework, which is likely to facilitate the hospital management in the operational implementation of the human resource-based theory. This theory facilitates the identification of the specific hospital mechanism, and processes, which enable the department in acquiring, developing, deploying, combining, and reconfiguring its physicians for achieving the sustainable competitive advantage (Barreto, 2010). The internal logic for the human resource-based theory is paradoxical in nature and demonstrates that the strategic value of human resource lies within the inherent complexities and the efforts which are performed for casually unravelling the complexities which are counterproductive. The intermediate constructs, including the dynamic capabilities, are required for preserving the strategic value of the human resource-based theory without negotiating the essence (Barreto, 2010). The implementation of dynamic capability framework offers an advantage to the hospital departments and directs hospital departments in combining, developing, and efficiently deploying the physicians for acquiring the competitive advantage.

Hospital physicians planning should take into account during pandemic like COVID three types of hospital physician's categories, COVID physicians and Non-COVID physicians and physicians in the emergency department (Affairs, 2020). It is true that physician's shortages, surpluses and wrong allocation for them affect the quality of health provided to patients, but the worst would be in case of wrong allocating (Suhail and Azhar, 2016). Physicians shortage problem gets more risky if a crisis like pandemic exists (White, 2002).

Gile et al. (2018) mentioned that the physicians management of the healthcare organizations must be efficient enough to identify the number of healthcare professionals, required for overcoming the burden of disease. Gile et al. (2018) mentioned that in most of the cases, the shortage of staff in the healthcare is due to the loopholes in human resource department to utilize the skills, experience and immunity for physicians working in the healthcare organization to enable them to deliver care services to the patients. Specifically, during the pandemic situations, the staff shortage contributes to the psychological ramification, including high levels of stress, anxiety, and burn out.

1.11.2 Number and Type of Departments

It has been reported that number and type of departments play a considerable role in making decisions related to human resource planning implementation (Tjosvold, 1988). The limited implementation of human resource planning practices in hospitals is perceived to be due to the lack of interest in making accurate classification of departments towards these practices (Morley and Cashell, 2017). Additionally, it is also observed that top or middle management demonstrating low levels of commitment also act as a barrier in making plan for number of departments needed in hospitals (Browning et al., 2016). Klopper-Kes et al. (2011) indicated that resistance to change current health organizational processes and avoidance towards planning for needed strong relation between the department's type and physician might be due to the lack of awareness and interest of top management towards their impacts on the hospital human resource. The implementation of departments plan practices require an active contribution of internal and external stakeholders within the hospital departments; therefore, planning for department's type and departments number requires monitoring of other factors such as physicians availability and behavior (Pandi-Perumal et al., 2015).

According to National Research Council report (2013), due to the shortage of departments within the healthcare organizations, the users of healthcare sector in the developed countries, such as the United States most often rely on the emergency departments for acquiring acute, preventive, as well as chronic care. In addition, another research by Bahadori et al. (2017) mentioned that due to an inadequate number of departments within the healthcare organization, most of the service users prefer acquiring care services from the outpatient departments. The inadequate manpower, and lack of accessibility towards the resources negatively influence the quality-of-care services delivered from the platform of the outpatient department within the healthcare care.

Halawa et al. (2020) mentioned that most addressed departments within the healthcare include the acute care inpatient units, the operating rooms, and emergency departments. However, all of the hospitals might not include the departments specialized for pandemic like COVID-19. Along with the analysis of the number of departments, the limited implementation of department planning within the healthcare industry also contributes to layout- related problems within the healthcare organizations. Some of the healthcare organizations deal with the layout-related problems by implementing the Quadratic Assignment Problem (QAP), which assures the availability of equal number of physicians for all departments (Halawa et al., 2020). In addition, depending on the physicians' number, and patients demand from the platform of the healthcare organization, the formation of layout for the departments with variable is carried out by using mixed-integer linear programming (MILP) (Halawa et al., 2020). Unlike other models and tools for capacity planning, MILP facilitates the management of layout related problems by assessing the potential number of service users in every department of healthcare, and arrange resources accordingly.

1.11.3 Immunity Rates

According to Smith (2014), immunity is the body's defense against infections and human immune system can be categorized into three types. The first type is innate immunity and this type reported to be the defense system with which you were born. It protects us against all antigens. The second type of immune system is adaptive immunity and this type human body develops when we're exposed to diseases or when we're immunized against them with vaccines. Whereas, the third type of immune system is passive immunity which is "borrowed" from another source and it lasts for a short time like antibodies.

Hospitals are the places where physicians are at high risk of contracting contagious infections (Nienhaus et al., 2012). Infection has a significant influence on hospital decision making, specifically regarding the implementation of resource planning practices (Farias et al., 2010). The previously-published researches regarding infection to human resource planning implementation mentioned that if infection is present in a hospital then it will affect the different kinds of patients and also other physicians (Blanchard, 2007). Moreover, workforce in healthcare sector significantly decreases during an outbreak since physicians will face a high risk of infection due to interaction with infected patients (Workers and Employers, 2009). However, the human resource planning can play a critical role in minimizing the danger, by planning resources in a fashion which ensures the safety of the community. There should be isolation wards for patients who have the highest chances for contracting or passing the contagious diseases (Dellinger, 2016).

According to van den Driessche (2017), infectious diseases are likely to be passed from one patient to the physician via respiratory droplets, body secretions, ingestion in food or water, and by biting of insects. Most of the infections can be controlled by vaccines, antibiotics, antiviral medications, reduction in vector population, increased sanitation, and several other strategies. Mathematical modelling is likely to play a significant role in quantification of the possible disease control strategies, by focusing on the significant aspects of the disease, determination of the threshold quantities for the disease survival, and evaluation of the effects of the control strategies (van den Driessche, 2017). The immunity factor is one of the most significant factors to be studied. Mathematical modelling performed by the health-care organization should facilitate this by arranging the physicians by their immunity for reducing the spread of infections from COVID patients to the other patients and health-care professionals.

The healthcare organizations can also utilize the outcomes acquired from adding this factor to the mathematical models for carrying out human resource planning for reducing the risk of spreading infections at the hospital(van den Driessche, 2017). In our research, this parameter based on the assumption that every physician is either with a high immunity, or has a low immunity and most of the infection’s physicians are with low immunity. For this reason, modelling using this factor is carried out during scheduling and allocating.

1.11.4 Skills and Experience

Skills and experience are also significant parts of the healthcare management. Maben et al. (2016) mentioned that the healthcare organizations emphasize on increasing skills and experience for physicians will increase the privacy, dignity, comfort, as well as less disruption for the patient for reducing the risk of spread of illness. Assigning physicians with high skills and experience is specifically beneficial during the pandemic situation. The availability of skills and experience within the healthcare organizations also have a significant influence on the quality of care services delivered by these organizations (Prin and Wunsch, 2012). The healthcare organizations having more number of skills and experiences are likely to provide care services to the patients more efficiently (Prin and Wunsch, 2012). The shortage of skills and experience in the COVID department during pandemic increases the rates of mortality. Specifically, during the pandemic situation, inefficient physicians allocating using skills and experience factors might reduce the quality-of-care services.

1.11.5 Lead Time and Waiting Time

Lead time can overall affects services quality (Darko and Lucy, 2018). Hassanzadeh Rad (2008) states that unnecessary movement, lack of training and unskilled employee, lack of standardized work and human resource planning make process inefficient and increase the moving time which is not clearly seen for the employee. Less emphasis of treatment time and real servicing time and accurate allocating for physicians result in lack of optimizing lead time expertise, which is a significant barrier to human resource planning practices’ implementation in the healthcare sector (WHO, 2018). Moreover, waiting is a defect which can overall slowed the hospital services quality and delay the patients and decrease their satisfaction (Pandit et al., 2016). Waiting is done due to a bottleneck station, breakdown of machine, material and staff shortage, not properly planning for uncertainty demand and not allocating physicians based on their practices (Petersson and Henningsson, 2015). In addition, Adamu and Oche (2013) mentioned that the most common factors contributing to long waiting time include a high load of the patient, unavailability of equipment, few healthcare professionals, as well as the prolonged registration process. Thus, the hospital management needs to emphasize on development and upgrading of relations between time and its physicians schedule (Sharifi, 2014).

According to Sun et al. (2017), the patient's waiting time reduces the overall quality of care services delivered form the platform of the healthcare organization; therefore, the healthcare organization have been strongly emphasizing on reducing the lead time. For instance, the Institute of Medicine of United States provided a framework of six guiding principles for staying ahead within the system of healthcare. The framework is also focused on arranging human resources for timely delivering care services and reducing the harmful delays (Sun et al., 2017). In addition, in the UK healthcare sector, the Patient Charter had set a series of standards, stating that all of the patients must be seen maximum within the initial 1 hour of the appointment time. In this regard, it is globally agreed that a well-designed healthcare management system needs to identify the factors contributing to increased waiting time for the patients (Viberg et al., 2013). These factors might include but are not limited to the shortage of physicians, the wrong scheduling for physicians for each department of the healthcare organizations, and lack of human resources analysis like the skills, experience, and immunity for the physicians and its effect on delivery of care services to the patients.

The research conducted by Al-Araidah et al. (2010) utilized the DMAIC (Define, Measure, Analyze, Improve, Control) principles for the identification of the factors contributing to a significant increment in the lead time within the healthcare organizations. Al-Araidah et al. (2010) discussed that DMAIC is a systematic six sigma process for improving the quality-of-care services, and comprised of various phases. The define phase of DMAIC is focused towards the identification of the projects which are critical for assuring quality, defining the process map, and development of the charter. In addition, the measurement phase defines the performance standards which are essential for assuring quality, collecting data and verification of the adequacy of the systems utilized for measuring lead time. Moreover, the analysis phase is focused on the identification of the gap between the physicians allocating process, which contributes to the identification of the root causes of increased lead time. DMAIC was found to be effective for reducing the lead time, and delivering quality care services; however, the efficient outcomes from DMAIC did not include the analysis of physician's level that include skills, experience, and immunity for selecting to achieve the optimum solution and reducing waiting time for patient.

1.11.6 Process and Tasks

The concept of work process denotes a set of repeatable value-creating activities for improving the quality of care services (Bergman et al., 2011). Within the healthcare organizations, the processes are analyzed with reference to the department, organizations, as well as from the industry perspectives. The healthcare organizations are perceived to utilize the available physicians for carrying out the processes of prevention, detecting health-related complications, diagnosing clinical complications, providing treatment, and facilitating the service patients with the good end of life. While carrying out planning for allocation of the available physicians in a best possible manner within the healthcare organizations, the healthcare management focuses on the system-wide view, and consider the impacts of the allocation of physicians on the interconnected departments (Bergman et al., 2011).

Specifically, during the pandemic situation, the intense focus of the healthcare sector is reducing the number of infected physicians and saving healthcare professionals and providing best health services for patients (Levin et al., 2007). For managing this situation, the healthcare organizations are responsible for performing efforts for raising awareness regarding the protective measures among the general population and assuring the utilization of physicians' protective within the healthcare settings. Levin et al. (2007) mentioned that during the pandemic situation, the placement of a large number of infected individuals within a congested setting might result in prioritization of the tasks, and processes within the healthcare sector during the pandemic which might differ from the duration of tasks without the pandemic. Thus, healthcare management is responsible for adjusting, and prioritization of tasks between the physicians and classification of processes between departments type taking place during the pandemic situation.

1.12 Capacity Planning in Hospital

Capacity planning is integral to every industry, specifically in the healthcare sector as it only correlates with the management of costly and highly efficient resources (such as healthcare professionals and medical equipment and devices) but also makes a stark difference between life and death in critical situations (Hulshof et al., 2012). Capacity planning specifically refers to the forecast and management of the demand with high precision to adjust the capacity or adopt alternate courses of action for managing patient influx. Capacity planning optimizes operational efficiency by limiting wastage and inefficiencies (Sharifi, 2014).

The capacity planning models implemented within the healthcare sector are most often based on department and physicians occupancy, and the number of beds presents within wards of hospitals (Rechel et al., 2010). Ettelt et al. (2012) discussed that the capacity planning models focused on the number of beds implies that the growing number of day cases, less occupancy of department, and the shorter duration of hospital stay are considered as the measure of capacity. However, these capacity planning models do not provide a good measure of the strategies implemented inside the hospitals for classification of patients and the physicians with reference to the complexity of the care services. Moreover, the capacity planning model based on the number of available physicians was not suitable for categorizing the physicians at an increased risk of infection for the physicians during pandemic, and the potential future demands of the resources within the healthcare (Rechel et al., 2010). Ettelt et al. (2009) fails to consider the allocation between the physicians and the best department. As the previous models of capacity planning did not include the physicians' immunity and the patient services; therefore, there was a requirement to implement the upgraded capacity planning models within the hospitals. For this reason, the capacity planning model is required to allocate the physicians by their skills, experience, and immunity and provide on-job training for delivering care services with full capacity, from the platform of the healthcare organization.

1.13 Service and Quality Level in Hospitals

According to McCord et al. (2015), service levels in hospitals can be categorized into three levels. The first level hospital was reported to have few specialties and limited laboratory services, and have the space of 50-250 patients. The first level hospital most often has the departments of, obstetrics, and general surgery, internal medicine, gynecology, and pediatrics but with very high waiting time for the patients. On the other hand, the second levels of hospitals comprised of 200 to 800 beds, and have the capacity to deliver care services for 5 to 10 specialties. Whereas, the third levels of hospitals comprised of highly-competent and specialized staff, and technical equipment for delivering specialized care services to the patients suffering from severe clinical complications. The third levels of hospitals have more difficulties to manage the high capacity with physicians scheduling (McCord et al., 2015).

During the pandemic situations, the healthcare organizations delivering care services at all levels are likely to contribute in management of the physicians with department to work efficiently to have a high quality service (McCord et al., 2015); however, the high quality service is more likely to be experienced by the management of all healthcare levels, due to its effect on patient satisfaction. For this reason, Khorshidi and Hejazi (2011) focus on delivering high quality services and customer satisfaction by minimizing waiting time (Khorshidi and Hejazi, 2011). Ghannadpour and Zarrabi (2019) study how to compute the perceived satisfaction levels for different type of customers or order (urgent and casual) using the earliest, latest, desired and actual time of service (Ghannadpour and Zarrabi, 2019).

1.14 Hospitals in Palestine during Pandemic

According to Hammoudeh et al. (2020), there was a severely intensified in the ongoing delicate political and economic state of the country by attacking the infrastructure that even includes healthcare facilities in the occupied Palestinian territory (OPT). The emergence of COVID-19 has integrated resource scarcity for the whole healthcare sector, especially including the hospitals. The country whose healthcare sector was itself handling a critical situation is now brought to the state of a double pandemic with the spread of novel coronavirus. The Palestinian Ministry of Health (PMoH) has played its substantial role in dealing with the pandemic having extremely scarce resources.

However, still, the OPT is being operated under an emergency condition. Also, the existing political context of the country confines the power and control of the Palestinian Authority (PA) over the borders (AlKhaldi et al., 2020). It becomes the prominent cause of why the country has observed imbalance in the diagnosis and prevention of the pandemic since not enough personnel protective equipment and testing tools have been supplied. Palestine has a lack of jurisdiction over the border and sovereignty in certain areas that eventually lead to limiting the ability of the healthcare sector of PA to manage the pandemic situation adequately. Therefore, it is critically important for the country to be provided with the best resource at the earliest of time so that better healthcare outcomes for the Palestinian citizens can be attained.

1.15 Summary

This chapter introduced the readers to sufficient knowledge about the supply chain, SCM in hospitals, their practices and the importance to improve the health care performance. This chapter presents many optimization and allocating models that aim to develop a physician's scheduling model in the healthcare sector to combat a pandemic state. The particular objectives of this research are to identify the primary model factors and parameters that are responsible for designing such appropriate models that can further help to attain the ideal healthcare outcomes. And then, using the significance of physicians' behavior as a factor that helps hospitals to improve their performance. Finally, the importance of studying the immunity, skills and experience for the physicians in implementing high service for the patients.

Chapter Two

Model Formulation

2.1 Overview

This chapter explains how the suggested model is mathematically-formulated. The Mixed Integer Linear Programming (MILP) was used to create the proposed model. At first, this chapter presents description of Mixed Integer Linear Programming model. And then, assumptions, sets, parameters, decision variables, objective function components and constraints are presented.

2.2 Mixed Integer Linear Programming (MILP)

The Mixed-Integer Linear Programming (MILP) model is utilized for system analysis, as well as optimization, and presents flexible and powerful method to solve large, and complex problems and the situations requiring process integration (Kantor et al., 2020). Due to a range of advantages, this system has been widely-utilized within the health-care systems.

The implementation of mixed-integer linear programming (MILP) models for resource planning was reported to facilitate in predicting the performance of health-care organizations, and the effects of structural, as well as parametric changes within these health organizations (Burdett et al., 2017).

2.2.1 Importance of MILP in solving Human Resource Planning

Human resource planning in health-care is referred to as the strategies utilized for avoiding shortfalls in the service for minimization of the expensive overruns. The process of human resource planning within the health-care is essential for managing the physicians, departments, as well as services for fulfilling the intended demands in the provision of care services (Burdett et al., 2017). Healthcare management has developed several approaches for carrying out system-wide analysis and efficient allocation for the physicians. The utilization of the models developed on intelligent systems for scheduling is likely to cause a significant improvement in the efficiency of hospitals in the future. The capacity planning initiatives which were taken previously were less focused towards the analysis of the risk of infection for the physicians, their skills and experience, classification of patients (Lin, 2008). However, the MILP model analyzes the physicians, classification of patients, and carries out the effect on waiting time and patient satisfaction on the basis of these factors.

2.3 Model Description

The proposed multi-department, multi-type of patients and multi-type of physicians' problem in a Human Resource Scheduling Model can be described as follows: the network consists of a set of physicians of various immunity, skills, experience. A set of departments of various types (Emergency department, COVID department, non-COVID department), a set of patients with different types that include patients in the Emergency department, COVID patients, and non-COVID patients. Also, there are a set of shifts types, we start by defining the shift time for each doctor in his/her expected special department. Waiting time for the patient is an index used to measure the physician's readiness in servicing the patient according to physicians classification issues, and there are some factors that might be used in minimizing patient waiting time such as awareness about allocating doctors based on their skills and experience in dealing with pandemics like COVID, and their immunity to reduce the transmission of infection from COVID patients to the doctor. Güler and Geçici (2020) showed that, the decisions that hospital takes such as strategic decision (i.e., scheduling issue), and we add in this model tactical decision and operational decision (i.e., physician selection based on physician behavior) and how this will affect patient's waiting time and therefore patient satisfaction. Also, service time and shift patterns. Huang & Rong Liu (2020) mention that during the pandemic situation like COVID, the healthcare physicians also experience the burden of delivering high-quality care services to the patients by using minimum service time. Moreover, working outside of the field of their practice might be other stressors for the limitation in giving high quality service of the healthcare organization. In this thesis, it is assumed that the three types of physicians' classification are different according to their skills patterns, the physicians of level one, have a high skills pattern in dealing with COVID patient, the physicians of level two have a low or moderate skill pattern in dealing with pandemic and COVID patient. Furthermore, the previous experience s/he has owned can influence the service time, the physicians of level one is classified as specialist in dealing with COVID patient, the physicians of level two is classified as residents. Providing immunity classification to protect physician from infection, will lead to improving their performance, and therefore improving their service time. So, the physicians of level one is classified as strong immunity physicians and they will deal with COVID patients in the COVID department, the physicians of level two are classified as weak immunity and they will work in the regular departments servicing non-COVID patients. Brunner and Edenharter (2011) mentioned that previous studies in the scheduling of physicians is not effective for assuring the basic of the human resource management system. The organization mechanism implemented within the healthcare, as the organizational hierarchy reinforces the parallel care processes, which fragment the human resource management practices as well as scheduling systems. Khatri et al. (2010) argued that the currently implemented Human Resource systems in the healthcare are based on the old industrial models of management, and are fairly inadequate for the management of knowledge-based as well as the service-intensive care entities.

The proposed model is to optimizing human resource planning process by allocating hospitals' physicians with the flow of patient's and department's type during a pandemic, and other uncertain situations also managing the relation between physicians' and minimizing the waiting time for the patient and increase patient satisfaction in the healthcare settings. So the problem is to determine: (1) best physicians to service in COVID Department in each shift, (2) the number of physicians that they should be at each department in each shift, (3) the shift time for each physician in his/her expected department, (4) the optimal assignment among physicians and departments by taking into account the patients types and the service time, so each physician's assign to one shift and only one department in the day and vice versa, so the model should select the optimum assignments in each period, and (5) the minimum total waiting time for each patient in order to increase patient satisfaction.

2.3.1 Model Assumptions

The model assumes the following:

1. During the physician's shift, there is no break time. Meaning that once the patient is out of the physician's office, the next patient enters immediately instantaneously.
2. Physicians who work in the COVID department actually works in one of the regular departments.

3. We assume that the epidemic situation has reached the steady state and the transient stage has ended, and accordingly, the rate of arrival of patient with COVID is constant, and that the average service time for each physician is fixed.
4. The patient who comes first is served first. (FCFS criteria).
5. Choosing a doctor to go to the COVID department depends on the degree of immunity (strong or weak), experience and skill s/he has, so that the more of these factors, the greater his/her chance of being allocated in the COVID department. Knowing that it was also assumed that increasing these factors is expected to reduce the waiting time for the patient.

2.3.2 Sets

Set	Description	Index
P	Set of the number of patients P	$p;\ 1 \ldots P$
D	Set of emergency departments.	$d;\ 1 \ldots D$
D_r	Regular departments in the hospital	r; $1 \ldots D_r$
D_c	COVID-19 departments in the hospital	c; $1 \ldots D_c$
T	Set of time periods.	$t;\ \ 1 \ldots T$
S	Set of shifts.	s; 1…S
Ir	Set of physicians who work in a regular department r.	-
Ic	Set of physicians who are qualified and eligible to work at COVID-19 department c.	-
Id	Set of physicians working in department d	-
G	Set of skills of physicians.	*g*= {1: high, 0: low}
H	Set of experience levels	*h*= {1: specialist, 0: residents}
M	Set of immunity system levels (according to vaccine shots).	*m*= {1: strong, 0: weak}

2.3.3 Parameters

Parameter	Description
Nd	Number of physicians required at department *d*
MDL_{rd}	The limit between the minimum and the maximum number of shifts of physician in regular department r in a month in department d.
MLL_d	The limit between the minimum and the maximum number of shifts in a month in department *d*
$Servicetimeh_{ghmp}$	Service time needed from a physician with skill *g* having experience *h* with immunity rate *m* needed to treat a patient *p*
$wait_p^{max}$	Maximum wait time allowed by patient *p*
λ_{ghmp}	Rate of arriving a patient p to be served by a physician with skill *g* having experience *h* with immunity rate *m*

$service$joint, s = $\sum_p \lambda_p(\vec{P}_p)$	The expected of joint exponential distributions, the first one represents the service time for 1st physician and the second for second. it indicates the number of patients during the same shift and in the same department.
$arrs$	Number of arrivals for patients in shift *s*
arr_p	The time point when patient p arrives the hospital and start waiting his/her turn.
x(t)	Number of dropped people at time *t*
u'_p	The desired time of service at patient node *p*
ω_p	Waiting time at patient node *p*
l_p	Latest arrival time within time window of service at patient node *p*
σ	Constant for violating the hard time windows.
f_p	Earliest arrival time within time window of service at patient node *p*.

2.3.4 Decision Variables

Decision Variables	**Description**
xh^t_{ghmp}	1 if a physician with skill *g* having experience *h* with immunity rate *m* needed to treat a patient *p* at a time *t*. 0 otherwise
$starth_{ghmp}$	Start treatment time of patient *p* by a physician with skill *g* having experience *h* with immunity rate *m*
U_{ghmt}	Deviation variable that allows rest for two consecutive days for a physician with skill *g* having experience *h* with immunity rate *m* needed to treat a patient in day *t*
$\boldsymbol{x}$init, s	Number of departure's patients who are still rest need treatment in the next shift.
$waith_p$	Waiting time at patient *p*
min ($service$joint, s| $x$init, s + arrs)	The minimum joint service time.
max ($service$joint, s| $x$init, s + arrs)	The maximum joint service time.
ε	The least difference between min and max service joint

Md_{rd}^{min}	Minimum number of shifts performed by a physician of regular department *r* at department *d* in a month
Md_{rd}^{max}	Maximum number of shifts performed by a physician of regular department *r* at department *d* in a month
ML_{d}^{min}	Minimum number of shifts performed by a physician at department *d* in a month
ML_{d}^{max}	Maximum number of shifts performed by a physician at department *d* in a month
X_{ghmtds}	Equals to 1 if physician with skill *g* having experience h with immunity rate *m* is working on shift *s* on day t at department d, 0 otherwise
J_{pt}	Penalty cost that hospital pays it if a patient p has waited more than *t* in any day, in any shift
$\mu_{\mathrm{p}}\,(t_{\mathrm{p}})$	Membership function of patient node *p*.
η_{p}	Control variable for each patient at node p.
at_p	Actual arrival time at patient node *p*.
t_{p}	Start time of service at patient node *p*.
$Sat.\,per_{\mathrm{p}}$	Real number where $Sat.\,per_{\mathrm{p}} \in [0,1]$ that shows the perceived level of patient satisfaction from the $_{\mathrm{p}}{}^{\mathrm{th}}$ dimension of service quality.

2.3.5 Objective Function

To minimize the waiting time for the patient which is the expected amount of the service time, which is as follows:

$$\text{Min w } = \text{P} \times \left(\sum_{p} servtimeh_{ghmp} \right) \times \, Jp, t \qquad (1)$$

2.3.6 Constraints

- Physicians can have at most one shift in a day:

$$\sum_{d} \sum_{s} X_{ghmtds} \leq 1 \qquad \forall g, h, m, t \qquad (2)$$

- Each shift in a department is allotted a sufficient number of physicians. This limitation also prevents non-eligible physicians from being assigned to departments. The allocation of physicians of various professions for COVID-19 shifts is a crucial problem for COVID-19 departments. For example, three physicians from neurology, brain surgery, and cardiovascular surgery can work on the COVID-ICU shift, but there can't be two cardiologists:

$$\sum_{g}\sum_{h}\sum_{m} X_{ghmtds} = N_d \qquad \forall t, d, s \tag{3}$$

- Between consecutive shifts, each physician has a day off:

$$\sum_{d}\sum_{s}\left(X_{ghmtds} + X_{ghm(t+1)ds}\right) \leq 1 \qquad \forall g, h, m, t \tag{4}$$

- If possible, this limitation gives two off-days between consecutive shifts. It's a soft limitation in the sense that if it's not practicable, the system won't arrange two off-days between successive shifts. The objective function minimizes the deviation in this constraint:

$$\sum_{d}\sum_{s}\left(X_{ghmtds} + X_{ghm(t+1)ds} + X_{ghm(t+2)ds}\right) \leq 1 + U_{ghmt} \qquad \forall g, h, m, t \tag{5}$$

- There is a minimum and maximum amount of shifts a physician can work in department *d* from a regular department *r*:

$$\sum_{t}\sum_{s} X_{ghmtds} \geq Md_{rd}^{min} \qquad \forall g, h, m \in Ir, d \in D, r \in D_r \tag{6}$$

$$\sum_{t}\sum_{s} X_{ghmtds} \leq Md_{rd}^{max} \qquad \forall g, h, m \in Ir, d \in D, r \in D_r \tag{7}$$

- There is a limit to the difference between the greatest and least number of these shifts:

$$Md_{rd}^{max} - Md_{rd}^{min} \leq MDL_{rd} \qquad \forall\, r \in D_r, d \in D \tag{8}$$

- The minimum and maximum number of COVID-19 shifts in COVID-19 Department *d* performed by a physician *e*:

$$\sum_{t}\sum_{s} X_{ghmtds} \geq ML_{d}^{min} \qquad \forall g, h, m \in I_d, d \in D_c \tag{9}$$

$$\sum_{t}\sum_{s} X_{ghmtds} \leq ML_{d}^{max} \qquad \forall g, h, m \in I_d, d \in D_c \tag{10}$$

- There is a limit to the difference between the greatest and least number of these shifts:

$$ML_d^{max} - ML_d^{min} \leq MLL_d \qquad \forall d \in D_c \qquad (11)$$

- If the difference between p's turn and his/her arrival time is less than T, s/he will get a service, else, s/he will be dropped. This constraint ensures that, the patients waiting time cannot exceed the allowable waiting in each period T:

$$J_{pt} = \begin{cases} 1 & t - arr_p \leq T \\ J(t) & t - arr_p > T \end{cases} \qquad \forall p, t \qquad (12)$$

- Service time for patient depends on the service rate of the physician *e*:

$$Servtimeh_{ghmp} = 1/\ \lambda_{ghmi}\ \text{, } i\ is\ the\ last\ atient \qquad \forall g, h, m, p, i \in p \qquad (13)$$

- Start time of patient *p* at shift *s* at physician e. Start time is the lowest value of *t* where xh is equal to 1. A patient will be treated (at a specific task) by a physician during many time periods. Suppose patient *p* requires psychiatrist for task trauma recovery at time periods 3, 4, 5, in this case the variable $starth_{ep}$ should get the minimum of (3,4,5), which is 3

$$starth_{ghmp} \leq\ t * xh^t{}_{ghmp} \qquad \forall\ g, h, m, p, t \qquad (14)$$

- When p0 arrives, the expected remaining service time for the current patient in physician = 1 \ 2* λ_{ghm} min(d):

$$E(servtimeh)_{ghmj} = 1/\ 2 \times \lambda_{ghmj} \qquad \forall g, h, m, and\ j \in p \qquad (15)$$

$$t = t_i - 1 + servtimeh_{ghm(i-1)}$$

$$servtimeh_{ghmi} = 1/\ \lambda_{ghmi}$$

- This constraint tells us the way that the patient p will be selected:

$$starth_{ghmi} = servtimeh_{ghm(i-1)} + starth_{ghm(i-1)} \qquad \forall\ g, h, m\ and\ i \in p \qquad (16)$$

- A patient can start treatment only after it arrives at the hospital. If patient arrived at the hospital at time period t, variable start cannot take 1 value for any t' lower than t, for all resources, all tasks:

$$starth_{ghmp} \geq arr_p \quad \forall\, g,h,m,p \quad (17)$$

- Maximum number of periods of wait allowed for patient:

$$waith_p \leq wait_p^{max} \quad \forall\, p \quad (18)$$

- The difference in service times for all shifts is as low as possible, and the adoption of service time is considered not only at the level of the doctor's performance, but also on the number of remaining members of the previous shift and the number of arrivals on the same shift:

$$\max\left(service_{joint,s} | x_{init,s} + arr_s\right) - min\left(service_{joint,s} | x_{init,s} + arr_s\right) < \varepsilon \quad (19)$$

- Based on the earliest, latest, desired, and actual time of service, Equations (20-22) show how perceived satisfaction levels are computed for different patients. The variable η_i is used to control if the start of service is before or after the desired time of service, constraints (20-22) are non-linear and should be relaxed to linear constraints according to Ghannadpour and Zarrabi (2019):

$$\mu_p(t_p) = \frac{(\mathrm{at_p} - \omega_\mathrm{p}) - \mathrm{f_p}}{\mathrm{u'_p} - \mathrm{f_p}}.(1 - \eta_\mathrm{p}) + \frac{\mathrm{l_p} - (\mathrm{at_p} + \omega_\mathrm{p})x^2}{\mathrm{l_p} - \mathrm{u'_p}}.\eta_\mathrm{p} \quad \forall\, p \quad (20)$$

$$\mu_p(t_p) = \frac{(\mathrm{at_p} - \omega_\mathrm{p}) - (\mathrm{f_p} - \sigma)}{\mathrm{u'_p} - (\mathrm{f_p} - \sigma)}.(1 - \eta_\mathrm{p}) + \frac{(\mathrm{l_p} + \sigma) - (\mathrm{at_p} + \omega_\mathrm{p})}{(\mathrm{l_p} + \sigma) - \mathrm{u'_p}}.\eta_\mathrm{p} \quad \forall\, p \quad (21)$$

$$\left(\mathrm{u'_p} \_ (\mathrm{at_p} + \omega_\mathrm{p})\right).\eta_\mathrm{p} \times ((\mathrm{at_p} + \omega_\mathrm{p}) - \mathrm{u'_p}).(1 - \eta_\mathrm{p}) < 0 \quad \forall\, p \quad (22)$$

The expected patient satisfaction performance which is calculated using equation below (Khorshidi and Hejazi, 2011)

$$Sat.per_p = \sum_p \mu_p(t_p) \quad \forall\, p \quad (23)$$

- The non-negativity constraints are given in Constraints (24).

$$ML_d^{max}, ML_d^{min}, Md_{rd}^{max}, Md_{rd}^{min}, starth_{ghmp}, waith_{ghmp} \geq 0$$

$$min\left(service_{joint,s} | x_{init,s} + arr_s\right), \text{max (servicejoint, s| xinit, s + arrs)} \geq 0 \qquad (24)$$

$$X_{ghmtds}, xh_{ghmp}^{t}, U_{ghmt}, J_{pt}, \in \{0,1\}$$

$$\varepsilon, Sat.per_p \in [0,1]$$

$$\mathrm{t}_p, at_p, \mu_p(t_p), \eta_p, \text{xinit}, s \geq 0$$

2.4 Summary

In this chapter, the proposed model for physicians scheduling model was described. This model was formulated as a mixed integer linear programing model (MILP). The developed model addresses multi-department, multi-type of patients and multi-type of physicians in hospital. This model's objective is to minimize the total waiting time for patient and reduce the probability of physician infection across the scheduling system in the hospital. This model also integrates physicians' differences in managing and scheduling planning at tactical and operational levels, for optimal selection of physicians, and then presenting the best assignment between physicians, patients and the departments to decrease the total service time across the supply chain network.

Chapter Three
Model Results

3.1 Overview

A numerical study is presented in this chapter to illustrate the validity of the suggested model. The description of the hypothetical problem is presented in this part. The results are created using the MATLAB program, as well as certain features of the MATLAB program and the “intlinprog” solver. Finally, in this part, the numerical results are shown and discussed

3.2 Hypothetical Data

The study was based on data collected from Güler and Geçici (2020), that include all of the characteristics and data required. The multi-type of physicians in the hospital intended to plan its scheduling taking shifts as periods, and dealing with a multi type of patients. The supply chain network consists of a set of physicians allocated based on their immunity, skills, experience in dealing with pandemics like COVID, three departments of various type (Emergency department, COVID department, non-COVID department), and three types of patients that include patient in the Emergency department, COVID patients, and non-COVID patients. We assumed that the numerical data used in the proposed model is known, as shown in Table 1. The number of physicians for each department, regular shifts, eligibility of departments in COVID-19 shift assignments are also presented in Table 2. The waiting time for each patient in each department are shown in Table 3. Also, finally, the percentage of patients' satisfaction with the services are shown in Table 4 as discussed in previous sections, μe(te) shows patient's satisfaction by measuring the deviation from the time of service using equations (20) and (21).

Table 1

(Numerical data used in the proposed model (Güler and Geçici, 2020))

Set Definition	Value
Set of physicians	81
t/T Index and set of days	30
d/D Index and set of departments	14
$s/S(d)$ Index and set of shift type for each department d	[2,2,3]
Ir Set of physicians working in regular department r	81
Ic Set of physicians eligible to work at COVID-19 department c	81
Id Set of physicians working in department d	55
Nd Required number of physicians at department d	[1 0 3 1;1 0 3 1;1 0 3 1;1 0 3 1;1 3 3 1;1 0 3 1;1 0 3 1;2 3 0 0;1 0 3 1;1 3 0 0;1 3 0 0;1 3 0 0;2 3 0 0;1 0 3 1];
DR Regular departments (such as orthopedics, internal medicine, etc.) in the hospital	14
DC COVID-19 departments (COVID-ICU, COVID-Service, COVID-Emergency) in the hospital	3
Meld The limit between the minimum and the maximum number of shifts of physician in regular department r in a month in department d	1
MLL_d	1

* The total number of required number of physicians at the 14 regular departments and COVID-19 shifts. The first cell gives required number of physicians at regular department in the hospital. The second cell shows the required number of physicians at COVID – ICU. The third cell shows the number of physicians needed at COVID – Service. The last cell shows the number of physicians needed at COVID – Emergency.

Table 2

Number of physicians for each department and eligibility of departments in COVID-19 shift assignments (Güler and Geçici, 2020)

Department	Num. of Physicians	Regular Shifts	Eligibility of departments in COVID-19 shift assignments		
			COVID-ICU	COVID-Service	COVID-Emergency
Orthopaedics and Traumatology	7	1	0	1	1
Urology	4	1	0	1	1
Eye Centre	7	1	0	1	1
Ear, Nose and Throat Disorder	5	1	0	1	1
General Surgery	5	1	1	1	1
Radiology	6	1	0	1	1
Psychiatry	6	1	0	1	1
Internal Medicine	7	2	1	0	0
Chest Diseases	4	1	0	1	1
Neurology	4	1	1	0	0
Brain Surgery	4	1	1	0	0
Cardiovascular Surgery	4	1	1	0	0
Cardiology	7	2	1	0	0
Pool	11	1	0	1	1

Table 3

The waiting time for each patient in each department in hours (Güler and Geçici, 2020)

	Department type																
Patient Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15 *	16 *	17 *
1	01:38	01:02	01:49	01:15	02:20	01:14		02:34	01:35	02:58	01:44	02:34	02:56	02:02	01:29	01:01	01:41
2	00:36	00:38	01:16	01:17	00:31			02:54	02:58	02:32	02:22	01:46	00:39	00:50	00:58	01:34	02:12
3	01:32	02:10	02:20	01:40	02:15			02:40	02:13	01:38	01:41	00:40	02:50	01:03	01:58	02:34	02:35
4	01:17	01:34			00:59			01:01	02:05	02:22	02:32		00:56	01:14		02:12	
5	02:55				02:22			01:11	00:49	02:59	02:58			02:35			
6	00:59				02:48						02:45			00:53			
7														01:02			
8														00:53			

*Three COVID departments of various type (15: COVID-ICU, 16: COVID-Service, 17: COVID-Emergency).

Table 4

The percentage of patients' satisfaction with the services

	Department type																
Patient Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15 *	16 *	17 *
1	85%	93%	86%	90%	81%	90%		78%	87%	70%	86%	78%	74%	84%	90%	93%	85%
2	95%	96%	90%	90%	98%			70%	70%	78%	81%	86%	95%	95%	95%	87%	82%
3	85%	82%	81%	85%	82%			78%	82%	87%	85%	96%	72%	94%	86%	78%	79%
4	90%	85%			95%			93%	84%	81%	79%		95%	90%		81%	
5	70%				81%			92%	95%	70%	70%			77%			
6	95%				72%						72%			95%			
7														94%			
8														95%			

*Three COVID departments of various type (15: COVID-ICU, 16: COVID-Service, 17: COVID-Emergency

3.3 MATLAB Solver and Algorithms

MATLAB deals with MILP as a problem with linear objective function that includes linear constraints, variables and constants. MATLAB also works as an optimization tool that provides multiple solutions for data modeling, and non - linear equations, linear regression, quadratic programming, complex and multi-objective optimization, non - linear least squares.

Heuristics algorithms provide a wide number of viable solutions (upper bound feasible solution) and Linear Programming (LP) techniques that provide a lower bound feasible solution. In addition, there is the "intlinprog" solution in MATLAB which is specifically designed to deal with the MILP problem, this way of solving used a variety of algorithms, including the Right-Hand Side (RHS), Gomory Cuts, Branch and Bound algorithms, Mixed Integer Rounding (MIR), MIR cuts, non-dominated sorting genetic algorithm II (NSGS-II) and others.

In this model we used the non-dominated sorting genetic algorithm II (NSGS-II) which is an additional characteristic in the genetic algorithm selection phase. Simulation results utilizing this method reveal that the proposed NSGA-II is capable of finding a considerably wider range of solutions in all issues than the excel solution utilized in addressing Güler and Geçici's (2020) model. The following sub-sections explain NSGA-II components: Population initialization, non-dominated sorting, Crowding distance, Crossover, Mutation.

The first step is to generate a random initial parent population P_0 with the size number of (N_{pop}); this population is generated depending on the problem range and constraints. The number of genes in a chromosome is equal to the number of decision variables in the model. In this model, facilities types include i*p where p is equal to summation of *g*, *h*, *m* where *g* is the skill, *h* is the experience and *m* is the immune needed to treat a patient.

In the second step the fitness function of the objective functions for each chromosome was measured after the random population was initialized. Then, in the non-domination function sorting operation, every chromosome is rated; the outcome is Pareto front. Every non-domination function is assessed to determine its non-domination level before rating the chromosomes, with level 1 being the best, level 2 the next best, and so on. The individuals/solutions are then split into two groups, the first of which contains all non-domination individuals with lower rank numbers. Folks on the second front have recently dominated individuals on the first front. The model has N number of objective functions in the case of a multi-objective function. The following is the procedure for comparing solutions: If X and Y do not dominate each other, they are put in the same front. However, X dominates Y if: X is not worse than Y for all objective functions, and X is strictly better than Y for at least one objective function.

The third step is crowding distance, if two or more solutions have the same rank, the crowding distance is utilized to pick between them, with the solution with the largest crowding distance being chosen. The crow's distance is a measure of the density of solutions surrounding a given solution, which can be computed using the following formula:

$$d_i^j = \sum_{i=1}^{N} \frac{f_j^{i+1} - f_j^{i-1}}{f_j^{max} - f_j^{min}}$$

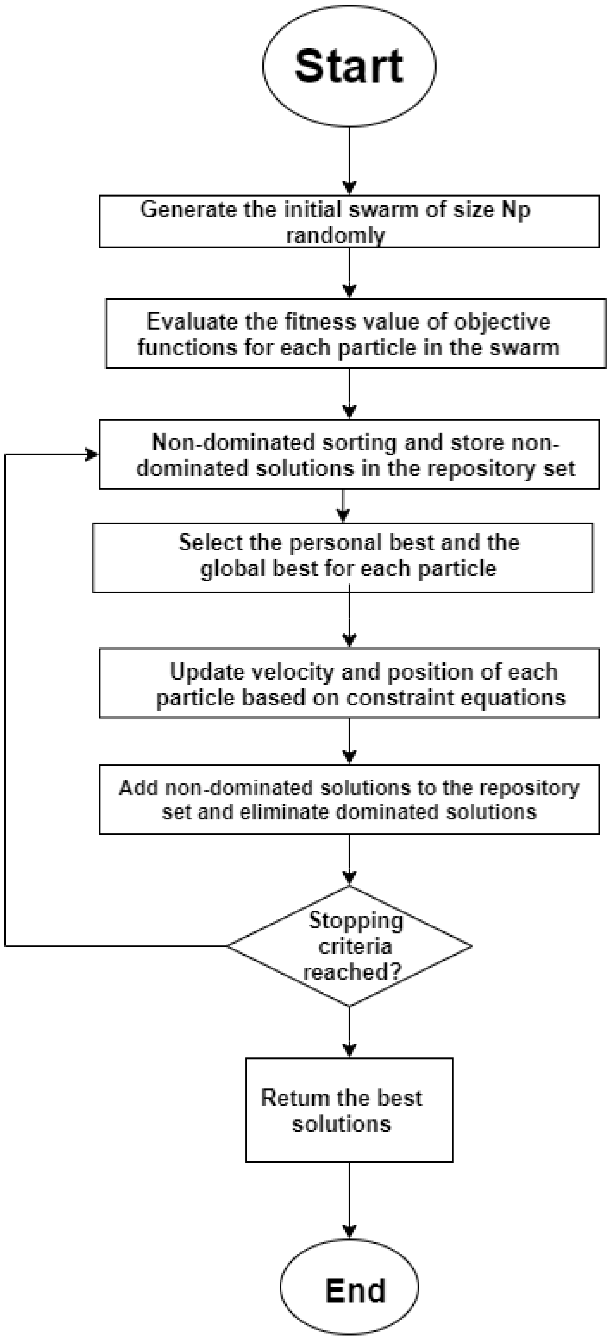
Where f_j^{max} is the minimum values of the objective function *j*, f_j^{max} is the maximum values of the objective function *j*, f_j^{i+1} is the value of objective function *j* of $(i + 1)$ solution, and f_j^{i-1} is the value of objective function *j* of (i − 1) solution.

After crowding distance, the crossover is an NSGA-II operator that is used to merge information from chromosomes (solutions) in order to maintain the development of the best solutions for complicated issues with a huge population of solutions. The crossover mechanism creates offspring or children's chromosomes from parent chromosomes. This method is based on using sections of parent chromosomes to generate kids, and if the best genes from parent chromosomes are used, the offspring may be better than both parents. A single-point crossover technique is used in this model, and it works as follows: a couple of Pareto front solutions are randomly chosen to be used as parents, a random point is chosen as a cross over point, the first part of the offspring chromosome comes from the first parent (parent 1), from the beginning of the chromosome to the crossover point, and the second part of the offspring comes from another parent (parent 2), from the crossover point to the end of the chromosome.

Finally, after the crossover phase, the mutation process works to increase the population's variety. A few genes were chosen at random and their values were changed as a result of a planned mutation. The mutation technique in this work is as follows: choose two random columns and swap them to create new offspring. Figure 2 presents a flow chart that explains the process of generating solutions using NSGA-II, which was adopted from the research of (Rabbani et al., 2018).

Figure 2

NSGA-II Flow Chart (Source: Rabbani et al., 2018).



3.4 Numerical Results

A non-dominated sorting genetic algorithm II (NSGS-II) was used in the computations using MATLAB. The following outcomes are obtained from the previously stated numerical study's data.

3.4.1 The assignments between physicians, departments and shifts.

Table 5 shows that the assignments between 81 physicians, departments and shifts for 1 month. Each physician will be assigned to his/her regular department otherwise the physician will be allocated to COVID departments based on their total level score. For example, 13 shifts for physicians' number 1 with total level 0 from ORT department were assigned to 13 shifts for regular department with no shifts in COVID departments. Physician number 5 from ORT department of level 3 was assigned to 8 shifts for COVID department and assigned to 6 shifts only to their regular department, etc.

Table 5

Physicians' type, shifts at each department with different skills, experience and immune level for each physician

No	Physicians	Total Shift	R	CICU	C-S	C-E	Skills	Experience levels	Immune system levels	Total level
1	ORT. Ph.1	13	13	0	0	0	0	0	0	0
2	ORT. Ph.2	15	6	0	3	6	1	0	1	2
3	ORT. Ph.3	14	6	0	5	3	1	1	0	2
4	ORT. Ph.4	15	5	0	4	6	0	0	1	1
5	ORT. Ph.5	14	6	0	3	5	1	1	1	3
6	ORT. Ph.6	13	8	0	3	2	1	0	1	2
7	ORT. Ph.7	13	3	0	6	4	0	1	1	2
8	URO. Ph.1	14	4	0	4	6	1	0	1	2
9	URO. Ph.2	14	1	0	1	12	0	1	1	2
10	URO. Ph.3	14	6	0	4	4	1	1	1	3
11	URO. Ph.4	14	9	0	3	2	1	1	1	3
12	EC. Ph.1	15	6	0	3	6	1	1	1	3
13	EC. Ph.2	14	6	0	6	2	1	1	1	3
14	EC. Ph.3	13	4	0	4	5	0	1	1	2
15	EC. Ph.4	15	4	0	7	4	1	1	1	3
16	EC. Ph.5	13	5	0	5	3	0	1	1	2
17	EC. Ph.6	13	4	0	5	4	1	0	1	2
18	EC. Ph.7	13	7	0	1	5	1	0	1	2
19	ENT Ph.1	13	4	0	5	4	1	0	1	2

20	ENT Ph.2	14	7	0	5	2	0	1	1	2
21	ENT Ph.3	14	2	0	7	5	1	1	1	3
22	ENT Ph.4	14	7	0	4	3	1	1	0	2
23	ENT Ph.5	13	2	0	5	6	1	1	0	2
24	GS. Ph.1	15	6	1	6	2	1	1	1	3
25	GS. Ph.2	15	3	6	6	0	1	1	1	3
26	GS. Ph.3	15	5	4	2	4	1	1	1	3
27	GS. Ph.4	15	6	4	1	4	1	1	1	3
28	GS. Ph.5	13	5	2	3	3	0	1	1	2
29	R. Ph.1	13	4	0	4	5	0	1	1	2
30	R. Ph.2	14	4	0	5	5	1	0	1	2
31	R. Ph.3	13	6	0	3	4	0	1	1	2
32	R. Ph.4	14	1	0	6	7	1	1	1	3
33	R. Ph.5	14	6	0	3	5	1	1	1	3
34	R. Ph.6	14	4	0	6	4	1	0	1	2
35	Psy. Ph.1	14	5	0	3	6	1	0	1	2
36	Psy. Ph.2	15	3	0	6	6	1	1	1	3
37	Psy. Ph.3	15	5	0	5	5	1	1	1	3
38	Psy. Ph.4	12	4	0	6	2	0	0	1	1
39	Psy. Ph.5	14	5	0	4	5	1	1	1	3
40	Psy. Ph.6	13	4	0	2	7	1	0	0	1
41	IM. Ph.1	15	9	6	0	0	1	1	1	3
42	IM. Ph.2	14	9	5	0	0	1	0	1	2
43	IM. Ph.3	13	6	7	0	0	0	1	0	1
44	IM. Ph.4	14	8	6	0	0	1	1	0	2
45	IM. Ph.5	13	5	8	0	0	0	0	1	1
46	IM. Ph.6	14	7	7	0	0	1	1	0	2
47	IM. Ph.7	14	10	4	0	0	0	1	1	2
48	CD. Ph.1	14	4	0	4	6	1	1	0	2
49	CD. Ph.2	14	6	0	6	2	1	1	1	3
50	CD. Ph.3	14	3	0	8	3	1	1	0	2
51	CD. Ph.4	15	2	0	9	4	1	1	1	3
52	N. Ph.1	14	9	5	0	0	1	1	1	3
53	N. Ph.2	12	6	6	0	0	1	0	0	1
54	N. Ph.3	14	7	7	0	0	1	1	0	2
55	N. Ph.4	15	9	6	0	0	1	1	1	3
56	BS. Ph.1	13	7	6	0	0	0	1	0	1
57	BS. Ph.2	13	6	7	0	0	1	0	0	1
58	BS. Ph.3	13	3	10	0	0	1	0	0	1
59	BS. Ph.4	11	5	6	0	0	0	0	0	0
60	CVS. Ph.1	13	4	9	0	0	1	0	0	1
61	CVS. Ph.2	12	6	6	0	0	0	0	0	0
62	CVS. Ph.3	13	8	5	0	0	1	1	0	2
63	CVS. Ph.4	12	5	7	0	0	1	0	0	1
64	C. Ph.1	13	8	5	0	0	1	0	1	2
65	C. Ph.2	14	7	7	0	0	1	1	0	2
66	C. Ph.3	12	6	6	0	0	0	0	1	1

67	C. Ph.4	15	6	9	0	0	1	1	1	3
68	C. Ph.5	12	6	6	0	0	1	0	0	1
69	C. Ph.6	13	8	5	0	0	1	0	0	1
70	C. Ph.7	11	5	6	0	0	1	0	0	1
71	Pool Ph.1	15	9	0	3	3	1	1	1	3
72	Pool Ph.2	13	4	0	2	7	1	1	0	2
73	Pool Ph.3	13	5	0	4	4	1	0	0	1
74	Pool Ph.4	13	6	0	3	4	1	0	1	2
75	Pool Ph.5	13	4	0	4	5	1	1	0	2
76	Pool Ph.6	13	7	0	1	5	1	0	0	1
77	Pool Ph.7	13	3	0	4	6	1	0	1	2
78	Pool Ph.8	15	9	0	5	1	1	0	1	2
79	Pool Ph.9	11	5	0	3	3	1	1	0	2
80	Pool Ph.10	13	4	0	5	4	1	0	0	1
81	Pool Ph.11	13	8	0	3	2	1	0	0	1

3.4.2 Workforce plan for physicians at regular and COVID department

The workforce plan for physicians related to number of physicians needed, number of shifts and patients. As shown in Table 6, COVID department does not include physician number 1 in the first week from orthopedics and traumatology department, because s/he has no skills, experience, and immune system. This leads to the number of shifts needed to deal with COVID patients for this physician which is equal to zero. In such a way that, the total number of shift for physicians' number 5 that are needed to handle COVID department is equal to 4 from ORT department because s/he has the skills, experience and immune system with total level equal to 3. This plan deals with the number of physicians needed from each department in each period at each COVID department, depending on each total level for each physician and the number of physicians. They should be allocated to cover the hospital demand during pandemic, because the model tried to trade-off between the selection of the physicians and their effect on waiting time for the patient. In regular department, the allowable total level of $physician\ number\ 1$ indicates to select the physician 1 of total level equal to zero to have more shift instead of COVID department in order to reduce the waiting time without any violation of the patient's satisfaction restriction. Therefore, the selection of physicians become more critical as the total level for skills, experience, and immune system differ and scheduling level become tighter, we will show that later in a sensitivity analysis chapter.

3.4.3 The actual waiting time for each patient after scheduling

In Table 7, the actual waiting time of each patient that required to be treated from the physician was calculated after scheduling depending on physicians' skills, experience, and immune level. For example, the average waiting time for patients decrease from one hour and 47 minutes to one hour and 5 minutes after scheduling.

3.4.4 The actual percentage of patients' satisfaction with the services

In Table 8, the actual percentage of patients' satisfaction with the services shows the interaction between decreasing waiting time and selecting the best physicians to treat patients based on their skills, experience, immune system and their effect on patient satisfaction with the service. The percentage of patient satisfaction with the service to each patient was calculated after scheduling. For example, for patient number 1 in department number 1 the satisfaction increased from 85% before scheduling to 90% based on choosing the best physicians to treat the patient and also decreasing the waiting time for this patient from one hour and 38 minutes to one hour and 8 minutes.

Physician selection based on differences leads to higher patient satisfaction since waiting times for all patients reduce and the improvement rate for patient satisfaction increased from 84 percent before to scheduling to 89 percent after scheduling.

Table 6

Physician's working schedule from the first department (Orthopedics and Traumatology)

	R			C-ICU			C-S			C-E		
Day	Shift 1	Shift 2	Shift 3	1	2	3	Shift 1	Shift 2	Shift 3	Shift 1	Shift 2	Shift 3
1	ORT. Ph.6		ORT. Ph.1					ORT. Ph.3		ORT. Ph.7		ORT. Ph.4
2											ORT. Ph.2	
3	ORT. Ph.7	ORT. Ph.4					ORT. Ph.3			ORT. Ph.5	ORT. Ph.6	
4	ORT. Ph.1											
5			ORT. Ph.3				ORT. Ph.2	ORT. Ph.5			ORT. Ph.6	ORT. Ph.5
6		ORT. Ph.1	ORT. Ph.4									
7			ORT. Ph.2				ORT. Ph.5	ORT. Ph.7				

Table 7

The actual waiting time for each patient in each department after scheduling (hr.)

	Department type																
Patient Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15 C	16 C	17 C
1	01:08	00:30	01:24	01:00	01:40	00:34		01:47	01:06	01:18	01:14	01:27	01:42	01:22	01:06	00:45	01:04
2	00:13	00:17	01:03	00:55	00:14			01:44	01:53	01:42	01:22	01:13	00:13	00:41	00:18	01:03	01:18
3	01:04	01:10	02:00	01:15	01:22			01:38	01:11	01:03	01:11	00:20	01:29	00:33	01:05	01:09	01:46
4	01:07	01:07			00:35			00:37	01:30	01:32	01:52		00:16	00:56		01:32	
5	01:26				01:19			00:27	00:19	01:19	01:45			01:30			
6	00:14				01:52						01:34			00:18			
7														00:42			
8														00:23			

*C: Three COVID-19 departments of various type (COVID-ICU, COVID-Service, COVID-Emergency).

Table 8

The actual percentage of patients' satisfaction with the services

	Department type																
Patient Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15 C	16 C	17 C
1	90%	95%	87%	92%	84%	96%		84%	92%	80%	90%	80%	84%	88%	94%	95%	89%
2	99%	99%	96%	94%	100%			82%	80%	80%	85%	89%	98%	98%	99%	92%	85%
3	89%	88%	79%	88%	87%			80%	84%	93%	89%	100%	82%	97%	92%	83%	83%
4	94%	88%			97%			95%	85%	85%	85%		100%	94%		84%	
5	83%				85%			94%	98%	83%	81%			85%			
6	98%				81%						81%			99%			
7														98%			
8														100%			

*C: Three COVID-19 departments of various type (COVID-ICU, COVID-Service, COVID-Emergency).

3.5 Sensitivity Analysis based on Physicians' Total Level

The sensitivity analysis is performed in this chapter, which means that the numerical parameters used to solve the model are evaluated, and then the results are discussed. The three major parameters are the focus of the sensitivity analysis which are the total level of physicians, the patient waiting time and patient satisfaction. The sensitivity analysis is performed after these sensitive parameters have been identified to examine how much the model's results are sensitive to changing in these parameters. So, the impact of the selection for physicians depending on their skills, experience, and their immune system on patient satisfaction and patients waiting time are analyzed.

A sensitivity analysis is performed in this section on the selection of physician based on their total level and its effect on the patient waiting time and patient satisfaction.

3.5.1 The effect of selection of physician on the patient waiting time.

In this section, we conducted a sensitivity analysis to examine the change in patient waiting time at each physician's level. At first, we put more waiting time to solve the problem, as expected, since there were the physicians allocated randomly with less total level that actually needed. After that, the waiting time gradually decreased and then analyzed the impact of selection based on physicians' total level on the patient waiting time. The results are shown in Figures 3 and 4, when the total level is 3 (the physician has skills, experience, and immune system to treat COVID patient), the average waiting time after scheduling become 29 minutes while it was 56 minutes before scheduling. In other words, the model minimizes the waiting time without any limitations on physician's total level, so the optimum solution is a tradeoff between physicians' selection (i.e., skills, experience, immune system), to minimize the patient waiting time and increase patient satisfaction. The physician's total level limit is not arbitrary value, but it could be explained as a human resource issue which hospitals have a willing to adopt, not including this human resource factors in scheduling could cost the hospital to loss patient and physicians too.

Figure 3

Physicians Total Level Against Average Patient Waiting Time Before and After Scheduling.

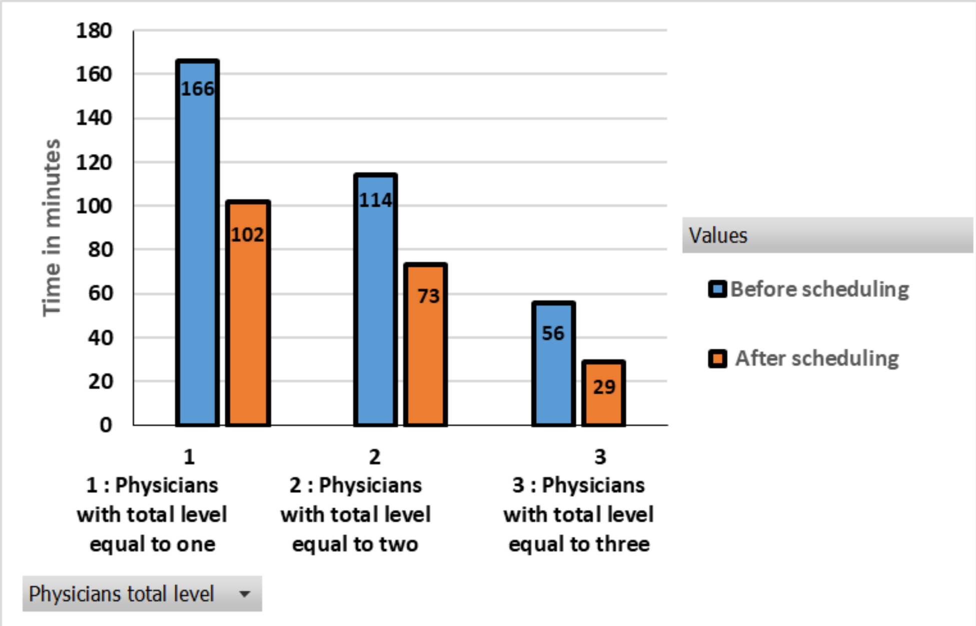
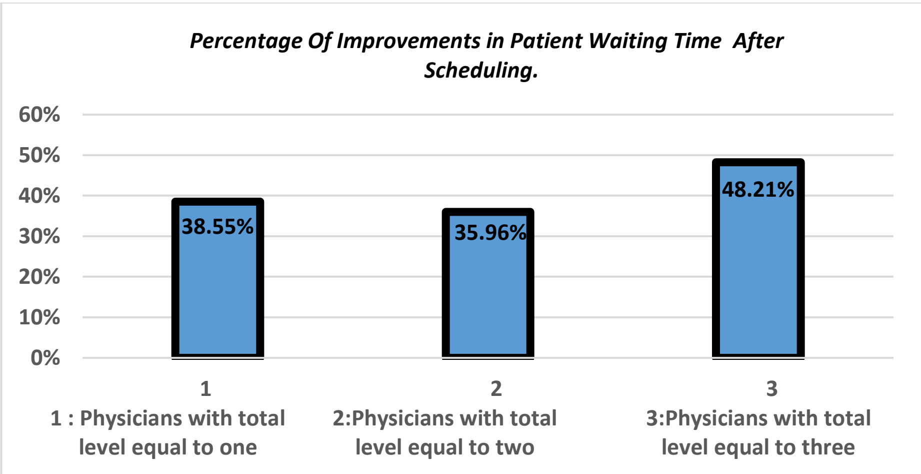


Figure 4

Physicians Total Level Against Percentage of Improvements in Patient Waiting Time After Scheduling.



3.5.2 The effect of selection of physician on patient satisfaction

A sensitivity analysis was carried out in this section on the number of physicians' total level which is needed to achieve the desired maximization in patient satisfaction. At first, we put a value for the allowable amount of percentage of patient satisfaction to solve the problem, and then, it has been increased gradually and analyzed the impact of this scheduling physicians from each level on patient satisfaction, as shown in Figures 5 and 6. As predicted, the result indicates that the model aims to maximize the patient satisfaction without any limitations on the physicians' issue, so the optimum solution is a tradeoff between the level of each physician and the effect of physicians from each level in patient satisfaction, so the physician's selection depends on the patient type and physicians' level. Before scheduling the percentage of patient satisfaction was (~ 74%) for level 1, level 2 with (~84%), and level 3 with (~94%). After scheduling the patient satisfaction is increased to become (~83%) for level 1, level 2 with (~88%), and level 3 with (~97%) among the total number of physicians that had been selected. This result indicates that, to which extent the hospital can achieve better service level depend on the number of physicians available from each n-level. This study has shown the importance of integrated HRM with HSCM, by selecting, training, classifying, scheduling, and performance evolution of physicians on development of a human resource scheduling model in the healthcare sector during pandemic.

Figure 5

Physicians Total Level Against Average Patient Satisfaction Before and After Scheduling.

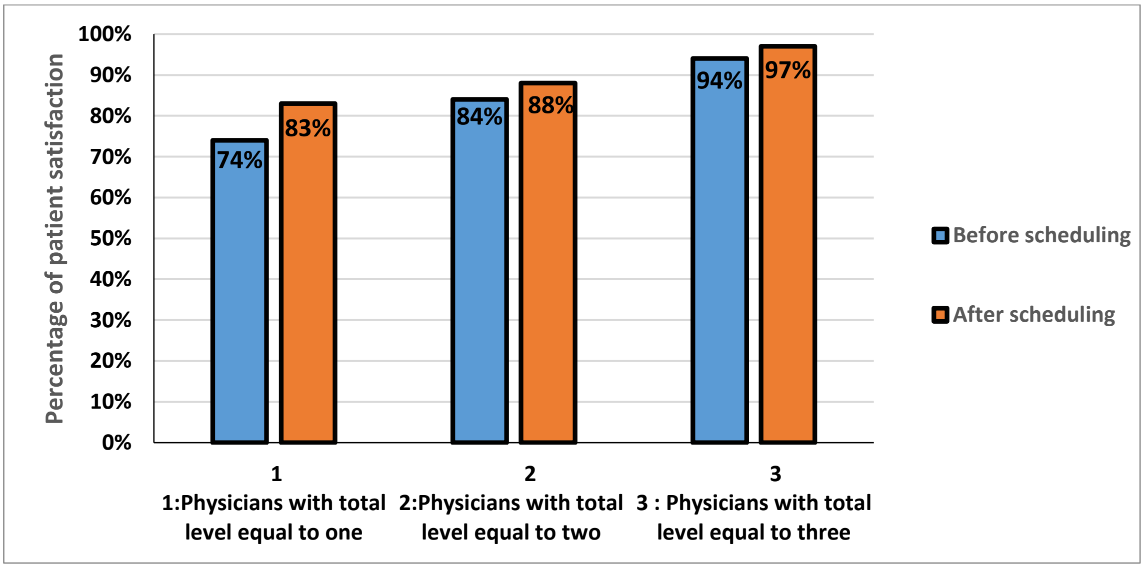
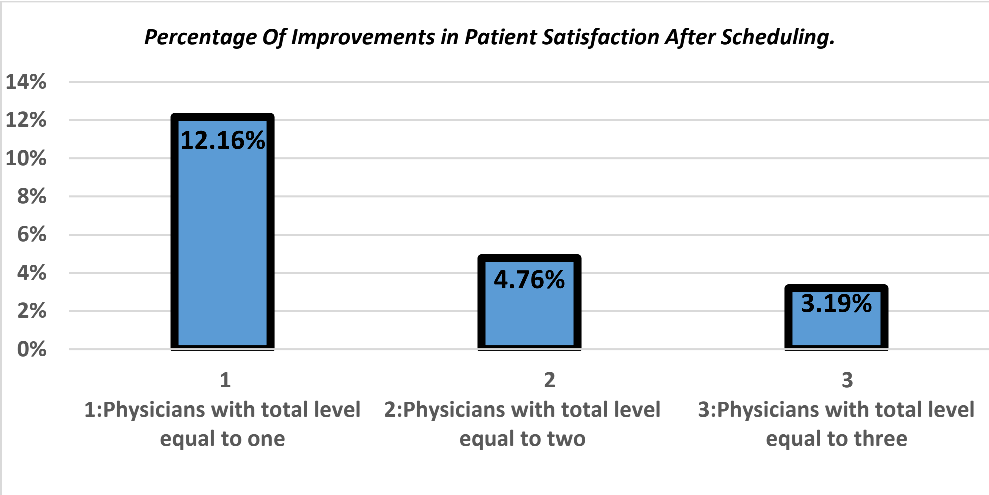


Figure 6

Physicians Total Level Against Percentage of Improvements in Patient Satisfaction After Scheduling.



3.6 Summary

The sensitivity analysis was presented in this chapter based on the numerical parameters utilized in the model. First, we did a sensitivity analysis on the total level for each physician depending on their skills, experience, and immune system, and its effect on the waiting time for patient. The results showed that, as the patient waiting time decreases the patient satisfaction percentage increases. Second, a sensitivity analysis is carried out on the physician total level and its effect on the shift selection of physicians. The results showed that, during pandemic the need to high level physicians is increased. This shows the significance of hospital in adopting the strategies to help hospitals to achieve the acceptable service level.

Chapter Four
Discussions and Conclusions

This chapter includes the discussion and contributions of study. At the end of this chapter, limitations, future studies are presented.

4.1 Discussions

This model demonstrated that setting priority between physicians is an essential aspect of human resource planning in the healthcare sector. The processes related to priority settings are required to incorporate the efficiency considerations for improving the service outcomes by using the available human resources. The research mentioned that after the method of prioritization of resources is required to be followed by an investment of the available human resources in the delivery of care. The investment in human resources is likely to improve the quality of health outcomes and reduce the patients waiting time. Thus, the emphasis of the healthcare organization on human resource planning is likely to have a positive influence on the supply chain management processes.

In this research, a novel approach for incorporating physicians' differences with aggregate planning in supply chain management is proposed. Some characteristics of the proposed model are as the following: (1) considering the major parameters of human resource as the degree of immunity, experience and skill the physician has; (2) considering the scheduling and shifts concepts in allocating; (3) considering physicians' levels in terms with different effect on patient waiting time and patient satisfaction; (4) considering the types of departments with different demand; (5) considering the assignment between physicians and COVID department.

The proposed model was formulated as a mixed integer linear programming, the model formulation and description were presented, and then a numerical study was conducted and solved to test the validity, applicability and solvability of the developed model. The results of this study were presented and discussed such that the number of physicians to be allocated from their regular department to COVID department, the scheduling plan physicians, and number of shifts. In addition, the sensitivity analysis was conducted on the patient satisfaction level, and the differences in waiting time. The results of conducting sensitivity analysis demonstrate that, after considering reducing the waiting time for patients the patient satisfaction was increased. Also, the number of physicians for each level varies with different patients’ satisfaction level, so the service satisfaction level that the hospital wants to achieve depends on the level of physicians' available which depends on their skills, experience, and immunity.

The results of this study are significant in a number of aspects. The proposed model conducts an optimal assignment between physicians, departments to reduce the patient waiting time, and increase the patient satisfaction with taking into account the differences impact of physicians and departments demand.

Specifically, during the pandemic situation, the implementation of human resource planning strategies fulfils the changing demands of healthcare and improves the accessibility of the population towards high-quality care services. This model demonstrates the significance of human resource planning, and human resource planning in hospitals especially human resource planning during the pandemic situations, and the frameworks which are utilized for human resource planning in the healthcare sector during the pandemic situation.

Development of human resource planning models in the healthcare sector is a key constraint during a pandemic. In this regard, this research aims to study and discuss the prominent models and frameworks used in the development of a human resource planning model in the healthcare sector to combat a pandemic state. The particular objectives of this research are to identify the primary model factors and parameters that are responsible for designing such appropriate models that can further help to attain the ideal healthcare outcomes. Critical analysis of MIP led to the investigation of the different mathematical models that were utilized to handle patient admission, scheduling programs, and scheduling of the physicians in emergency department.

This model is significant for improving the match between the physicians to the needs of patients. This model is also a significant determinant of the satisfaction levels of the patients. Initially scheduling process in the healthcare was confined to the appointment for acquiring inpatient, and outpatient care services; however, this model, schedule the process including the analysis of physicians. Another advantage of this scheduling process is that it facilitates analyzing the manner in which the physicians present at the hospital, schedule appointment, and provides high priority care services to the service users. The model utilized in the healthcare sector facilitates which allows the utilization of human resources for scheduling the physicians within specific times of the day. However, this model is required to implement within the healthcare departments on the basis of the availability of physicians and patient flow.

4.2 Research Contributions

This research contributes to the literature with a realistic model that takes physicians selecting, assigning to departments in scheduling and planning at tactical and operational levels. Previous researches completely ignored the differences of human aspects in terms of (skills, experiences, immunity) between physicians in scheduling during pandemic. Differences in satisfaction metrics can explain for variation in patient impressions of hospital treatment, since there are six dimensions for patient satisfaction in hospitals (i.e. Safety, Effectiveness, Efficiency, Patient preferences, Equity and time). This model's patient satisfaction focuses on "Effectiveness, Efficiency, and Time”. This approach allows us to address integrating physicians’ differences in terms of skills, experiences and immunity rates to get the best scenario for selecting and assigning physicians to fulfill a hospital’s aims for reducing their patient waiting time and improve patient satisfaction. Better previous skills of medical staff were linked to lower patient waiting time and higher patient satisfaction, so classifying them by whether or not they attended workshops aimed at training medical staff about dealing with pandemic and infected patients' skills and attitude of medical staff will increase the rate of satisfaction, and the same for experiences by classifying them by whether or not they are epidemiologist or not. Immunity tests revealed that reducing infection risk is strongly dependent on the amount of vaccination doses the physicians received before. Therefore, this research provides decision-makers with a more realistic model. This model will support the hospital’s management with a sufficient knowledge about how to deal with pandemic.

4.3 Limitations

This model was found to efficiently contribute to minimize patients waiting time with different severity of clinical complications and is likely to determine the requirement of physicians’ number and make arrangements for human resources. The implementation of this MILP model might also facilitate the healthcare organizations in analyzing their capacity for delivering high-quality care services.

In spite of the model's strengths, the proposed model has a number of limitations. These limitations and the proposed recommendations can be described as follows:

- Although the model gives valid results, it is relied on data from related literature that represents the researchers' experience.
- All parameters in the developed model are assumed to be known such as waiting time and physicians' level. Solving the model using real cases may decrease the uncertainty in this model. Patients' satisfaction surveys should be conducted on a regular basis in all sectors of health care in order to enhance service quality. If a hospital collected the kind of information outlined here on each physician on a regular basis, it would offer clinicians, management, and trustees with specific, actionable information about areas where treatment may be improved.

4.4 Future Works

The opportunity is still existing to develop the proposed model. The proposals for future research can be described as follows:

- Implementing the proposed model by using stochastic version to know the exact importance of integrating physicians' differences in improve the hospital service.
- It's clear that human factors (HF) in health sector have much more research opportunities, and the path is still open to making a mathematical model that incorporate HF in term of physicians' performance such as infection rate and fatigue rate which can be a promising area of future work.

List of Abbreviations

Abbreviation	Meaning
SCM	Supply Chain Management
SCMHC	Supply Chain Management in Health Care
WHO	World Health Organization
MILP	Mixed Integer Linear Programming
DEA	Data Envelopment Analysis
MIP	Mixed-Integer Programming
HR	Human Resources
HRM	Human Resource Management
ED	Emergency Departments
BBO	Biogeography-Based Optimization
OR	Operations Research
OPT	Occupied Palestinian Territory
PA	Palestinian Authority
OM	Operations Management
PMOH	Palestine Ministry of Health

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جـامعـــة النجاح الوطنية

كليـــة الدراســـات العليـــا

تطوير نموذج رياضي لجدولة المرضى وإدارة موارد قطاع الرعاية الصحية بطريقه مثلى أثناء الجائحة في فلسطين

إعداد

لنا وائل غنام

اشراف

د. محمد عثمان

قدمت هذه الأطروحة استكمالا لمتطلبات الحصول على درجة الماجستير في الادارة الهندسية في كلية الدراسات العليا

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الملخص

قد حظيت سلاسل الامداد على اهتمام كبير من الباحثين في العقود القليلة الماضية في المجال الطبي وقطاع المستشفيات، ولكن تم تجاهل تأثير الجوانب البشرية للطبيب في ادارة سلاسل الامداد وجدولة الأطباء والمرضى. في هذا البحث، تم تطوير نهجا جديدا لدمج اختلافات الاطباء من خلال الخبرة ودرجة المناعة والمهارات لدراسة تأثيرهم على وقت الخدمة الخاص بالمريض بعد تصنيف المرضى في ظل جائحة كورونا وتقليل وقت الانتظار للمرضى. اضافة للعمل على تقليل احتمالية اصابة الطبيب بفايروس كورونا من خلال ادخال عامل مناعة الطبيب في الجدولة. وبشكل اكثر تحديدا، تم اقتراح نموذج رياضي خطي مختلط من المتغيرات الصحيحة وغير الصحيحة يراعي اختلاف المستويات بين الاطباء و اختلاف انواع المرضى. النموذج يهدف لتقليل الوقت الكلي للانتظار وتحسين رضى المريض عن الخدمة. وبالإضافة الى ذلك، يهدف النموذج لمساعدة اصحاب القرار في القطاع الصحي في بناء السياسات وعمل الخطط اللازمة خلال الجائحة. تم التأكد من صلاحية النموذج المقترح وقابليتيه للتطبيق. وأظهرت نتائج تحليل الحساسية، أن عدد الأطباء المطلوبين من كل مستوى وتوزيعهم حسب الخبرة والمهارات ومستوى مناعة الطبيب على كل قسم يختلف باختلاف عدد المرضى الذي يتم توزيعهم

على الاقسام لذلك فأن مستوى الخدمة التي تسعى المستشفيات لتحقيقه يعتمد على مستوى الاطباء وتصنيفهم حسب وجدولتهم بطريقه فاعله حسب ما هو متوفر لديها.