Big data analytics and the effects of government restrictions and prohibitions in the COVID-19 pandemic on emergency department sustainable operations

Görkem Sariyer[1] · Mustafa Gokalp Ataman[2] · Sachin Kumar Mangla[3] ·
Yigit Kazancoglu[4] · Manoj Dora[5]

Abstract

Grounded in dynamic capabilities, this study mainly aims to model emergency departments' (EDs) sustainable operations in the current situation caused by the COVID-19 pandemic by using emerging big data analytics (BDA) technologies. Since government may impose some restrictions and prohibitions in coping with emergencies to protect the functioning of EDs, it also aims to investigate how such policies affect ED operations. The proposed model is designed by collecting big data from multiple sources and implementing BDA to transform it into action for providing efficient responses to emergencies. The model is validated in modeling the daily number of patients, the average daily length of stay (LOS), and daily numbers of laboratory tests and radiologic imaging tests ordered. It is applied in a case study representing a large-scale ED. The data set covers a seven-month period which collectively means the periods before COVID-19 and during COVID-19, and includes data from 238,152 patients. Comparing statistics on daily patient volumes, average LOS, and resource usage, both before and during the COVID-19 pandemic, we found that patient characteristics and demographics changed in COVID-19. While 18.92% and 27.22% of the patients required laboratory and radiologic imaging tests before-COVID-19 study period, these percentages were increased to 31.52% and 39.46% during-COVID-19 study period. By analyzing the effects of policy-based variables in the model, we concluded that policies might cause sharp decreases in patient volumes. While the total number of patients arriving before-COVID-19 was 158,347, it decreased to 79,805 during-COVID-19. On the other hand, while the average daily LOS was 117.53 min before-COVID-19, this value was calculated to be 165,03 min

✉ Yigit Kazancoglu
  yigit.kazancoglu@yasar.edu.tr

1 Yasar University, Department of Business Administration, İzmir, Turkey

2 Bakırçay University Çiğli Region Training and Research Hospital, Department of Emergency Medicine, İzmir, Turkey

3 Digital Circular Economy for Sustainbale Development Goals (DCE-SDG), Jindal Global Business School, O P Jindal Global University, Haryana, India

4 Yasar University, Department of Logistics Management, İzmir, Turkey

5 Sustainable Production and Consumption School of Management Anglia Ruskin University, Cambridge, UK

🖄 Springer

during-COVID-19 study period. We finally showed that the model had a prediction accuracy of between 80 to 95%. While proposing an efficient model for sustainable operations management in EDs for dynamically changing environments caused by emergencies, it empirically investigates the impact of different policies on ED operations.

Keywords Big data analytics · Emergency department · COVID-19 · Machine learning · Sustainable operations

1 Introduction

Medical scientists and sociologists have widely researched the effects of the COVID-19 pandemic on human physical and psychological health. Its impacts on operations and supply chain management have gained significant attention from scholars (Choi, 2021; Queiroz et al., 2020; Sarkis, 2021) and industry experts (Deloitte, 2020; Harvard Business Review, 2020). However, although the COVID-19 pandemic has affected operations and supply chains on a large scale and most the companies have faced disruptions (Fortune, 2020) since it has also created emergency situations in many countries, its impact on health services is a high priority and needs to be addressed.

Efficient and timely service delivery is a significant burden for health services, and the importance of providing rapid responses increases in emergencies. However, as experienced during the COVID-19 pandemic, this is very challenging, particularly for EDs, which are increasingly used as gateways to hospital admissions and have been identified as one of the most overcrowded health services units. Besides, since most countries provide a 7/24 ED service, non-urgent patients frequently occupy them, which has also been identified as an essential issue leading to increased overcrowding (Ataman & Sariyer, 2021). While the problem of overcrowding in EDs is a major challenge for the service providers even in regular times (Sariyer & Ataman, 2020), pandemic environments push these services into bottlenecks since the number of patients being infected increases uncontrollably. In addition to this sharp increase in patient volumes, the profiles and demographics of patient admissions to hospital EDs also vary significantly. Under these circumstances, to protect the functioning of health services and EDs, governments are forced to impose widespread restrictions and prohibitions. To cope with the COVID-19 pandemic, the leaders of many countries declared sudden or phased lockdowns and quarantines and the closure of physical shops and businesses, transport bans, etc. Although these may help the functioning of EDs under emergencies and cause a sudden decrease in patient volumes, it is crucial for ED service providers to rapidly adapt the system in response to such changes and be able to manage operations efficiently in highly dynamic conditions (Alinaghian & Goli, 2017; Hossain et al., 2021; Mondal & Roy, 2021; Thakur et al., 2021). Thus, not only but especially under emergencies, EDs must have strong dynamic capabilities to manage these uncertain and dynamically changing environments.

These huge patient volumes and the extensive range of patient characteristics also create large volumes of data for EDs. Thus, these health services are additionally challenged by a ubiquitous context of big data, which has appeared as an exciting frontier of productivity and opportunity (Sanders & Ganeshan, 2018). In this era, data is also identified as a valuable asset of EDs, enabling insights and decision making (Feng & Shanthikumar, 2018). However, big data requires the ability to process and arrange it to be used in decision-making. Thus, although the collected data is precious for EDs, unless they can analyze it and transform it into useful information that can be turned into rapid action, it cannot go beyond useless data

recording that simply takes up storage capacity. At this point, BDA becomes increasingly crucial for EDs in making efficient and timely decisions in emergency situations.

The term 'BDA' is used to refer to the techniques, technologies, systems, practices, methodologies, and applications for analyzing big data sets and is defined as a holistic process of collecting, managing, and investigating the five major dimensions of data: volume, variety, velocity, veracity, and value (Wamba et al., 2017). BDA can support operational and strategic decision-making and turn to action in value creation for all organizational levels and enhance operational performance. BDA technologies have been implemented for various operations and supply chain practices based on their superior performances (Gupta et al., 2021; Kumar et al., 2016, 2020; Marić et al., 2021; Mishra et al., 2018). In the big data era, BDA can be viewed as an organizational capability for EDs to cope with dynamically changing situations. Thus, besides having strong dynamic capabilities, if an ED holds BDA capabilities to manage big data, it should respond more actively to emergencies, increasing its efficiency and performance in managing operations. Moreover, big data and BDA implementations in real-time systems will have great importance in providing sustainable ED operations (Das et al., 2021; Goli et al., 2019, 2021; Midya et al., 2021; Mondal & Roy, 2022). Having such capabilities and advantages, BDA has attracted researchers, decision, and policymakers in coping with COVID-19 as a current global emergency (Abdel-Basset et al., 2021; Bag et al., 2021; Huang et al., 2020; Kapoor et al., 2021; Lee & Trimi, 2021; Mondal & Roy, 2021; Papadopoulos et al., 2020; Sharma et al., 2020; Sözen et al., 2022; Tirkolaee et al., 2022).

Although these technologies are popular in the COVID-19 context, they have little use in the ED operations decision-making processes in this pandemic period. On the other hand, since EDs are the main actors of health services in managing emergency environments, taking advantage of these technologies to improve EDs' operations is critical in effectively managing emergencies. Besides, since governmental reactions in fighting COVID-19 have caused sharp and significant changes in the demand for EDs, investigating the effects of these actions in EDs operations and putting these effects into account in decision-making models is another unique point. Therefore, this study aims to present a model implementing BDA technologies for managing four primary ED operations in COVID-19. By conducting interviews with ED service providers and searching the related literature, the primary operations that are challenging for ED services in emergencies and even in regular times are determined as managing daily patient volumes, average stay lengths of patients, and utilization of laboratory radiologic imaging services. Besides proposing a generic model for managing ED operations under emergencies and validating this model for different processes of EDs, taking the governmental actions as the main factors of this model and thus showing how they affect these operations is the novelty of this paper. Hence, we aim to answer the following research questions in this paper:

RQ1. How does BDA assist in making effective decisions for predicting daily patient volumes, average stay lengths of patients, and resource utilization of EDs under dynamically changing conditions caused by emergencies?
RQ2. How do government-imposed restrictions and prohibitions affect daily patient volumes, average stay lengths, and ED resource utilization of EDs in emergencies?

Since the current emergency having worldwide effects is the COVID-19 pandemic, we focus on modeling ED operations during COVID-19 and identify the restrictions and prohibitions imposed to cope with this pandemic. To address these research questions, we propose a BDA-driven model and implement machine learning techniques as one of the most potent sub-set of BDA. More specifically, we implement neural networks-based techniques and multilayer perceptron (MLP) algorithms to develop required predictions on daily patient volumes,

average stay lengths, and daily utilization of laboratory and imaging services of EDs. In validating this model in different ED operations, we define the output variables for each operation as previously stated and identify two sets of factors (input variables). While in the first set, we identify possible operation-specific factors that may affect the output variable of this operation. We define additional elements representing different types of government restrictions and prohibitions in the second set. These factors are similarly used for each operation. With the proposed model and implemented MLP algorithm by obtaining 80% to 95% accuracies for predicting the output values of four ED operations, we answered the RQ1 of this study since such accurate predictions play a crucial role in making efficient decisions EDs under emergencies. By investigating the significance of the relations between the output variables and the set of input factors representing the government-imposed restrictions and prohibitions and analyzing the directions of these relations, we answered the RQ2 of this study.

The organization of this paper is as follows. In Sect. 2, we discuss the theoretical background of this paper. We present the proposed model in Sect. 3 and introduce the case study, and data set characteristics, data pre-processing steps, and results of the proposed model in Sect. 4. Section 5 discusses the findings of this study. We present the theoretical, managerial, and policy implications in Sect. 6. Section 7 offers concluding remarks, limitations of this study, and the future research directions.

2 Theoretical background

2.1 The dynamic capabilities view

Dynamic capabilities define an organization's ability to innovate, adapt to change, and improve in a good way for its customers (Teece et al., 2016). Zollo and Winter (2002, p. 340) defined dynamic capability as a "learned and stable pattern of collective activity through which the organization systematically generates and modifies its operating routines to pursue improved effectiveness."

The dynamic capabilities utilize an organization's internal and external resources in the best possible manner to respond appropriately to environmental uncertainties (Teece et al., 1997). Emergencies cause environmental or external uncertainties, and managing operations in EDs, particularly under emergencies, requires real-time information whereby service providers can arrive at critical decisions. The dynamic capabilities help integrate primary resources through the availability of this information and then further help to modify ED operating routines and procedures appropriately. Therefore, we based our research on the dynamic capability view. Positioning the resources correctly is the prime requisite for coping with these uncertainties and the chaotic environments related to emergencies. Dynamic capabilities are the main processes for sensing, integrating, learning, and reconfiguring resources and capabilities (Birkinshaw et al., 2016) and stress an organization's capacity to create, extend or modify its resources purposefully. These are also crucial in managing ED operations, particularly in emergencies, since aligning the capabilities and resources and reconfiguring the processes may help dynamically deal with changing patient volumes and profiles. To deal with unexpected increases in patient volumes in COVID-19, many countries reconfigured their health systems, so pandemic services were opened to provide patients. The resources and capacities of these services, such as doctors, nurses, and other health staff, required medical equipment (medicines, beds, intensive care units, respiratory devices), were provided by many different hospital departments and mainly from the EDs. In some countries where pandemic services were not opened, EDs served as these services and encountered COVID-19

patients. For such countries, the increased need for medical staff and resources was satisfied by reconfiguring the hospital's other services and aligning them with the pandemic services.

In the health services operations and supply chain management literature, many studies base their theoretical backgrounds on the dynamic capability perspective (Rubbio et al., 2020). In the era of big data, health systems are one of the primary services that deal with big data sets of the high volume, variety, and velocity of patient data. Thus, we move further towards BDA capability (BDAC), which has evolved from the dynamic capability perspective. We, therefore, highlight the importance of having BDAC for managing health services operations, particularly in emergencies.

2.2 Big data analytics capability

During the COVID-19 pandemic, BDA has been used to detect surface indicators related to the pandemic (Guo et al., 2020). Real-time big data-driven insights have helped scholars and decision-makers to comprehend the impact of this pandemic. COVID-19 trackers provide an essential source of data to help scholars research and make more informed decisions on coping with this pandemic by collecting and aggregating big data (Verma & Gustafsson, 2020). Such situations increase the volume and the variety of patients' characteristics in health services. Besides, many external factors may come into play, changing the system dynamics. Under such circumstances, it is necessary for health services providers to rapidly adapt the system to the changing conditions to provide timely and effective services to patients. Thus, the role of BDAC in healthcare operations gained increased attention (Yu et al., 2021).

We propose a system for managing ED operations, such as forecasting patient volumes, analyzing patient LOS, and modeling the use of primary resources in emergencies. Even in regular times, the main challenge faced by ED service providers is the overcrowded environment of these services, which creates vast volumes and varieties of patients. An emergency is an external challenge that may cause an unexpected and sharp increase in patient volumes and varieties, thus straining the system and making managing operations much more difficult. Government is a prominent actor as a system enabler in this era. To protect the functioning of these services and respond to emergencies, governments impose some policies, such as restrictions and prohibitions, which may cause a sudden decrease in patient volumes but still change the characteristics and increase the system's randomness. All these create dynamically changing environments, and the service providers must adopt the system appropriately and effectively in response to these rapidly changing conditions. Since by their nature and due to all these sudden changes, ED services include a huge volume, variety, velocity, and veracity of data, these services may take advantage of BDA to help operations cope with such rapid changes in the system. We summarise the theoretical framework of our research in Fig. 1.

As seen in Fig. 1, based on huge volumes, velocities, and varieties of patients, the data inherent in the EDs exhibits a dynamic feature. Since emergencies are also featured with rapidly changing conditions, these increase the randomness in the EDs and, therefore, stalemate decision-making processes in EDs. This study attempts to contribute to dynamic capability theory and BDAC by extending their usage for the decision-making processes of one of the most important actors of health services, EDs, under emergencies. By presenting the rapidly changing features of the EDs in emergencies and presenting a model highlighting a need for BDAC, this study aims to contribute to the context of these theories.
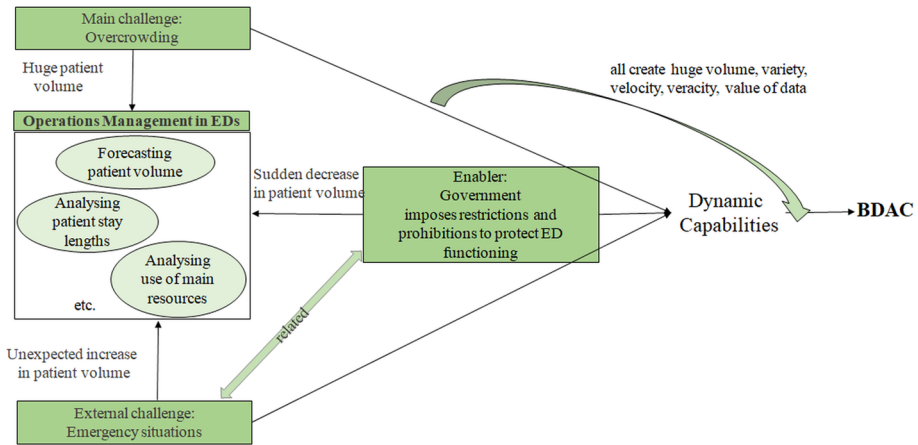
Fig. 1 Theoretical framework of this research

3 Proposed models

In this paper, we propose models for managing the primary operations of EDs, particularly in emergencies. These models include five main sequential steps: Data Collection, Pre-processing, Modelling, Testing & Model Evaluation, and Providing Managerial & Policy Implications. As discussed earlier, ED environments contain big data sets that can be processed with BDA, and valuable information can be obtained in decision-making. Thus, an essential initial step for adapting these emerging technologies into proposed models and systems is bringing data sets related to the context. A data set can be obtained using different sources within this research framework. To get the related data of the proposed models, we required data triangulation. Valuable data sets for the proposed models are secondary data received from a case ED covering the period before and during COVID-19; government reports; documentary analysis; and interviews with ED service providers. Case study data may include relevant information about patients arriving at this ED during the study period. Government reports and documentary analyses should be checked to identify the types of restrictions and prohibitions imposed by the government to cope with the emergency. Finally, interviews and documents should be used to decide on the main challenges to ED operations, making planning and managing operations more difficult in emergencies. Related metrics and targeted values of these metrics can also be identified by collecting data through interviews and a literature search.

Since the collected data is raw data, which in its current form is not suitable for analyzing and modeling, different data pre-processing tasks must be performed. It is necessary to define the input and output variables of the model, define the periodicity (hourly, daily, weekly, monthly, etc.) of the analysis, and determine ways to measure the values of the variables. Data transformation may also involve measuring the values of the variables. One of the main pre-processing tasks in big data studies is cleaning the data set to remove redundant or inappropriate data, missing values, and outliers. After all these tasks have been performed, the structured data set, which can further be processed with BDA tools and techniques, is obtained.

Once the structured data set of the model is ready, the modeling step comes next. The obtained data set is split into two train and test sets. Train data sets include the values of all the input and output variables, whereas since the test data set will be used to evaluate the model's prediction accuracies, it does not include the values of the output variables. The

train data set is further processed with machine learning as one of the most widely used BDA techniques. Machine learning presents algorithms to extract knowledge and make efficient decisions by learning from given data sets. Researchers widely prefer these algorithms based on their flexibility in using data to capture complex and non-linear behaviors (Choi et al., 2018). Among various machine learning algorithms, MLP neural networks have received significant attention since these are appropriate and efficient for function approximation, pattern classification, and prediction. Incorporating hidden layers between input and output layers is one of the other parser properties of these algorithms. When required by extending the number of hidden layers, MLP neural networks can expand the number of input feature combinations to improve the model's learning ability, finally increasing the prediction power. Although many other BDA techniques have been widely implemented in the literature, the machine learning-based MLP neural network algorithm is integrated into the proposed model based on these properties and superiorities.

The testing and model evaluation step comes next in the proposed model. The obtained MLP algorithm with the optimized parameters is applied to the test data set to get the predicted values of the output variables of interest. The predicted values are then compared with the actual values, and the mean errors and accuracies of the prediction should be calculated. These performances should then be compared with the target values. If the targets are achieved or the model performance goes beyond the targeted one, the model can be proposed for real-life applications. The results on the significance and impacts of government restrictions and prohibitions may also be discussed in detail, and implications should be recommended to policymakers. Suppose the model performance cannot achieve the targets. In that case, it is necessary to go back to the data pre-processing step and re-define the model input and output variables. The modeling, testing, and evaluation steps must be repeated until proper models have been obtained. The proposed model is shown in Fig. 2.
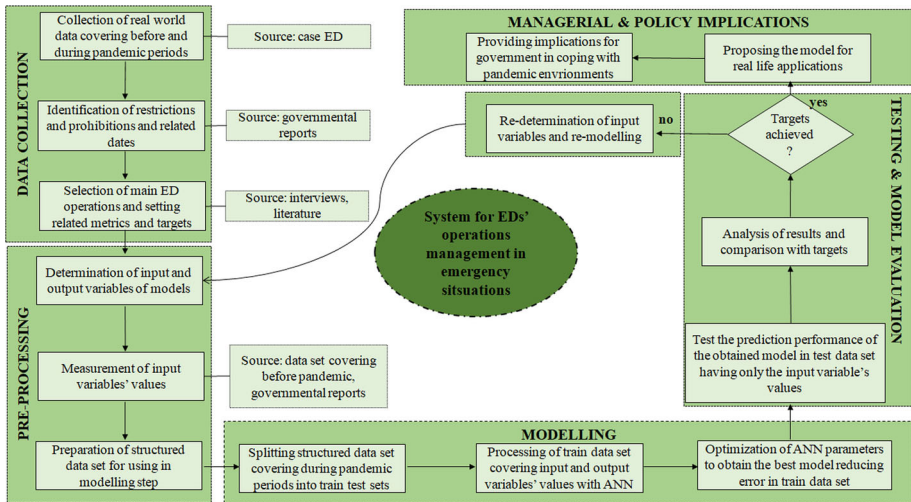

Fig. 2 Flowchart of the proposed model

4 Case study

4.1 Case study specification

We collected the data set of this study from an ED of a research and training hospital located in a metropolitan region in Izmir, Turkey. The daily number of patients or visits to this ED is more than 1,000. This huge patient volume is due to several reasons. First, as mentioned previously, overcrowding is a common problem in EDs. Second, due to the vast volumes of non-urgent patient visits, this problem can be more severe in some countries, such as Turkey, compared to many other countries. Third, many patients may choose to be treated in this hospital due to its type. Fourth, since this is a public hospital, receiving service from EDs is free of charge. Fifth, since it is located in a metropolitan region and is very close to public transport stations and the city center, it is also easily accessible for ambulances. Sixth but not least, since this ED provides uninterrupted service (7 days and 24 h) while many of the other departments of this hospital provide service only within working hours on weekdays, this causes additional visits of patients of different departments to EDs out of the working hours. These characteristics created huge volumes, velocities, and varieties in the data set.

In Turkey, the first COVID-19 case was reported on March 10, 2020, in Istanbul city, and the virus then spread quickly to the whole country. In Turkey, the COVID-19 was encountered later than in many other countries. Thus, public awareness had already been created about this virus and the pandemic. Public awareness was a crucial initial step in coping with this virus. Since it first appeared in Turkey, the government started announcing policies like "social distancing," "hygiene," and "stay at home." However, raising public awareness from the outset and making announcements was not enough to prevent the spread of the virus. Then, the government imposed other types of restrictions and prohibitions. Restrictions for the elderly, inter-city transport bans and restrictions for the young were imposed starting from the end of March. In addition, starting from the middle of April, total curfews were imposed at weekends (for two days) and for extended weekends in some of the weeks, which could last up to three or four days. The number of cases and deaths started to fall by May. Then the period of normalization began at the beginning of June. Although restrictions and prohibitions were still in use during this month, they were more relaxed.

Having high volumes, velocities, and varieties in patient sizes and characteristics, the selected ED was identified as proper for this study's theoretical framework and methodology. Besides, since in different periods (such as before March and during April) and days (such as weekdays and weekends), government-imposed actions were highly changing during the study period, the case ED allowed to investigate the impact of these actions on ED operations.

4.2 Data set characteristics

The data set covers seven months, from December 2019 to June 2020, and includes 238,152 patients. Data from between March 10 to the end of June 2020 represents data collected during the period of COVID-19's first peak in Turkey. To have a similar number of days before the COVID-19 period, the related data set was started in December 2019. Thus, before COVID-19 and during COVID-19 periods cover around 3.5 months of data. For each arriving patient, records of the ED case include the following information: patient ID, gender, age, arrival type, triage level, date of arrival, time of arrival, diagnostic tests for treatment-if required, related times for diagnostic tests, assigned diagnosis type by a doctor after treatment, and time of departure. The patient ID is unique for each patient arrival. Gender is recorded as

male and female. Age is recorded as it is in a continuous form. The arrival type represents if a patient arrived by themselves or by ambulance, so it is recorded as one of two options: "walk-in" or "by ambulance." When a patient comes to this ED, they are first met by a triage nurse, who triages the patient based on his complaints and clinical acuities. This ED uses the 3-level Emergency Severity Index for patient triage.

Furthermore, trauma patients are treated in a different zone. Thus, arriving patients are assigned to one of four zones labeled green, yellow, red, and trauma zones. The arrival date represents the full date of the patient's arrival in a day, month, and year form. Time of arrival shows the exact time of arrival in an hour, minute, and second form. Many diagnostic tests can be ordered in EDs for patient diagnosis. The label of the requested test, and the related ordering time, approval time, and result time are recorded in the next three rows in an hour, minute, and second form. When doctors diagnose the patients, they assign the type of diagnosis based on the International Classification of Diagnosis 10th version (ICD-10). Thus, the diagnosis cell includes the diagnosis based on the ICD-10 codes, which can have 22 different categories. The last cell consists of the departure time of the patient in an hour, minute, and second form.

The data set includes additional attributes to represent government restrictions and prohibitions. The four main restrictions and prohibitions imposed in Izmir city are considered in the proposed models. During the COVID-19 study period, total curfew (lockdowns), curfew for the young (age ≤ 20), curfew for the elderly (age ≥ 65), and transport bans were imposed. These are also adopted in the proposed models as model input variables, as discussed in the next section on data pre-processing.

As presented in Fig. 2, selecting the study variables is an important initial step of the proposed model. However, it should be kept in mind that these variables are not fixed and rigid and may depend on the selected case studies. Different variables may define the system's internal and external dynamics for other cases.

4.3 Data pre-processing

We implement the proposed model with four different ED operations to investigate how the imposed policies have changed and affected the primary operations and resource usage. The first and second operations, Operation 1 and Operation 2, respectively predict the daily number of patients arriving and the average LOS of these patients (LOS is defined as the time between the patient's arrival and their departure) for each day during-COVID-19 period. Different diagnostic tests can be mainly grouped into either laboratory tests or radiologic imaging tests. Thus, we also implement the model for two other operations to analyze the primary resource usage. Operation 3 and Operation 4 predict daily numbers of ordered laboratory tests and radiologic imaging tests for diagnosing patients. Regarding output variables or attributes of the model for each operation, these are defined adequately as the daily number of patients, average daily LOS of patients, the daily number of laboratory tests ordered, and the daily number of radiologic imaging tests ordered during-COVID-19 period.

Since the aim is to model and manage related daily values, the data set was initially transformed. In this process, we eliminated the repetitive values from the data set. More than one ICD-10 encoded diagnosis can be assigned to a patient. Different laboratory tests (hemogram, biochemistry, enzyme, hormone, etc.) or radiologic imaging tests (X-ray, tomography, ultrasound, magnetic resonance imaging, etc.) can also be ordered for a patient with a unique ID. While obtaining the corresponding daily value of the models, we eliminated these repetitive or redundant values.

Besides the policy-based attributes, some other input variables were also defined to adopt the system characteristics in the proposed models. These variables were used to represent the system dynamics in normal circumstances. Previous studies showed that the day of the week has a significant effect on patient volume and LOS (Sarıyer et al., 2020). Existing literature also presented that the patient volume, LOS, and numbers of diagnostic tests ordered differed significantly between categories of demographic variables (Sarıyer & Ataman, 2020). We, therefore, identified these factors as internal factors to represent the ED environment in normal circumstances. To measure the values of these inputs, we used the study's data set covering the before-COVID-19 period. As in output variables, we made the required transformations to obtain the daily values of these input variables. The data set is described in Table 1.

We performed data pre-processing by dropping missing values in the dataset by using the *dropna()* function of the *pandas* module in Python. After this, based on standardization, we removed the outliers from the data set by using the *zscore()* function of the *pandas* module

Table 1 Definitions and measurement scales of the model variables

Operation	Defined output variables (symbol, definition, scale)	Operation-specific input variables representing system dynamics (symbol, definition, scale)	Common input variables (symbol, definition, scale)
1: Managing daily numbers of patient	Y1: The daily number of patients arriving each day in the during-COVID-19 study period (numerical)	X1: The average daily number of patients arriving for each day of the week—Monday through to Sunday (numerical)	*Representing government restrictions and prohibitions* X2: The whole curfew exists in the day to be predicted or not (categorical) X3: Curfew for young exists in the day to be predicted or not (categorical) X4: Curfew for the elderly exists in the day to be predicted or not (categorical) X5: Transport ban exists in the day to be predicted or not (binary)
2: Managing daily average LOS of patients	Y2: Average daily LOS of patients arriving each day in the during-COVID-19 study period (numerical)	X7-X8: average daily LOS of female-male patients for each day of the week (numerical) X9-X10-X11: Average daily LOS of age groups—[0–14], [15–64], ≥ 65—for each day of the week (numerical)	

Table 1 (continued)

Operation	Defined output variables (symbol, definition, scale)	Operation-specific input variables representing system dynamics (symbol, definition, scale)	Common input variables (symbol, definition, scale)
		X12 through X15: Average daily LOS of triage groups—red, yellow, green, trauma zones—for each day of the week (numerical)	
		X16 through X37: Average daily LOS of ICD-10 encoded diagnosis, for 21 groups*, for each day of the week (numerical)	
3: Managing daily numbers of ordered laboratory tests	Y3: The daily number of laboratory tests ordered in the during-COVID-19 study period (numerical)	X38-X39: Average daily numbers of laboratory tests ordered for female-male patients for each day of the week (numerical)	
		X40-X41-X42: Average daily numbers of laboratory tests ordered for age groups—[0–14], [15–64], $\geq$ 65—for each day of the week (numerical)	
		X43-X44: Average daily numbers of laboratory tests ordered for arrival type groups—by ambulance or walk-in—for each day of the week (numerical)	
		X45 through X48: Average daily numbers of laboratory tests ordered for triage groups; red, yellow, green, trauma zones, for each day of the week (numerical)	

Table 1 (continued)

Operation	Defined output variables (symbol, definition, scale)	Operation-specific input variables representing system dynamics (symbol, definition, scale)	Common input variables (symbol, definition, scale)
		X49 through X69: Average daily numbers of laboratory tests ordered for ICD-10 encoded diagnosis, for 21 groups*, for each day of the week (numerical)	*Representing system dynamics* X1-fcast: Predicted daily number of patients with Model 1 on each day during-COVID-19 study period (numerical) –used in 2nd, 3rd, and 4th operations modeling
4: Managing daily numbers of ordered radiologic imaging tests	Y4: The daily number of radiologic imaging tests ordered in the during-COVID-19 study period (numerical)	X70-X71: Average daily numbers of radiologic imaging tests ordered for female-male patients for each day of the week (numerical)	
		X72-X73-X74: Average daily numbers of radiologic imaging tests ordered for age groups—[0–14], [15–64], ≥ 65—for each day of the week (numerical)	
		X75-X76: Average daily numbers of radiologic imaging tests ordered for arrival type groups—by ambulance or walk-in—for each day of the week (numerical)	
		X77 through X80: Average daily numbers of radiologic imaging tests ordered for triage groups—red, yellow, green, trauma zones—for each day of the week (numerical)	
		X81 through X101: Average daily numbers of radiologic imaging tests ordered for ICD-10 encoded diagnosis, for 21 groups*, for each day of the week (numerical)	

in Python. We initiated the categorical conversion of the input variables with the *Categorical* class initializer of the *pandas* module in Python. We used the *Categorical* class to encode numerical values as categorized by the capability of initializing the corresponding variables with categorical values. After these pre-processing steps, we obtained the structured data set for further modeling with the MLP neural network.

As seen in Table 1, we identified the government policies as common input variables in each operation to analyze their effects on each of the defined output variables for the corresponding operations. However, once we predicted the daily number of patients in Operation 1, we used these predictions to describe system characteristics in all other models. The daily number of patients may affect the average daily LOS, and the number of each diagnostic test ordered.

5 Results

5.1 Descriptive results

The study period covering the before-COVID-19 period included 100 days of data, and the total number of patients arriving during these days was 158,347. Laboratory tests were ordered for 29,953 of these patients and 43,106 radiologic imaging tests. On the other hand, the study period covering the during-COVID-19 period included 113 days of data, and the total number of patients arriving during these days was 79,805. The number of laboratory and radiologic imaging tests ordered during this period was 25,154 and 31,488. The average daily LOS was 117.53 min in the before-COVID-19 period and 165,03 min in the during-COVID-19 period. Daily values for the number of patients, average LOS, and numbers of each type of diagnostic test ordered in the whole study period are depicted in Fig. 3.

These results show that while daily and total numbers of patients and diagnostic tests ordered sharply decreased, average LOS values increased during the during-COVID-19 period compared to before-COVID-19. However, although decreases are seen in three of the operations' output variables (1, 3, 4), the sharpest decline was seen in Operation 1's output, the daily number of patients. The decrease in patient numbers may have also caused the decline in the number of tests ordered. On the other hand, it should be noted that, although patient and diagnostic test numbers decreased, average LOS values increased. All these critical numerical findings could be due to the change in the system dynamics, which were mainly caused by patients who occupied EDs unnecessarily and did not need an emergency service.

We categorized the patients into three groups to support this idea by numerical findings consistent with our model boundaries and comparatively presented the related statistics for
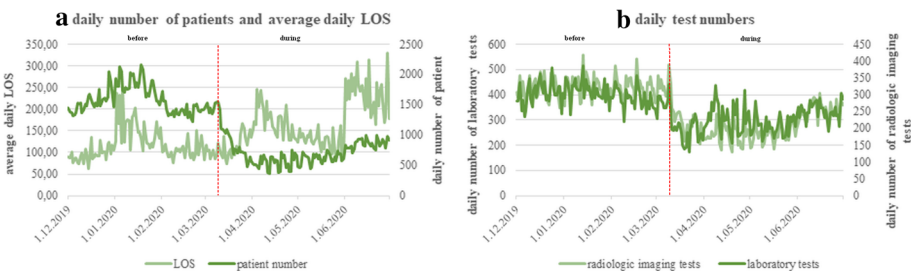

Fig. 3 Daily values of the models' output variables in the study period

each of these. These categories were: patients requiring no diagnostic tests, laboratory tests, and radiologic imaging tests. Since diagnostic tests are one of the most critical resources for diagnosing patients, we believe most patients for whom no tests are ordered can represent the cases that occupy EDs for non-urgent conditions.

For these categories, the average daily numbers of patients and their average LOS are shown for each day of the week before-COVID-19 and during-COVID-19 periods in Fig. 4.

Figure 4 shows that while average daily values for patient numbers decreased in each of the three categories in the during-COVID-19 period compared to the before-COVID-19 period, the majority of the decrease is related to the category of patients requiring no diagnostic test. Although it is worth noting that reductions were seen in the number of patients requiring no diagnostic test, some increases were seen in their average LOS values in the during-COVID-19 period. This finding mainly supports our hypothesis. On the other hand, at least some
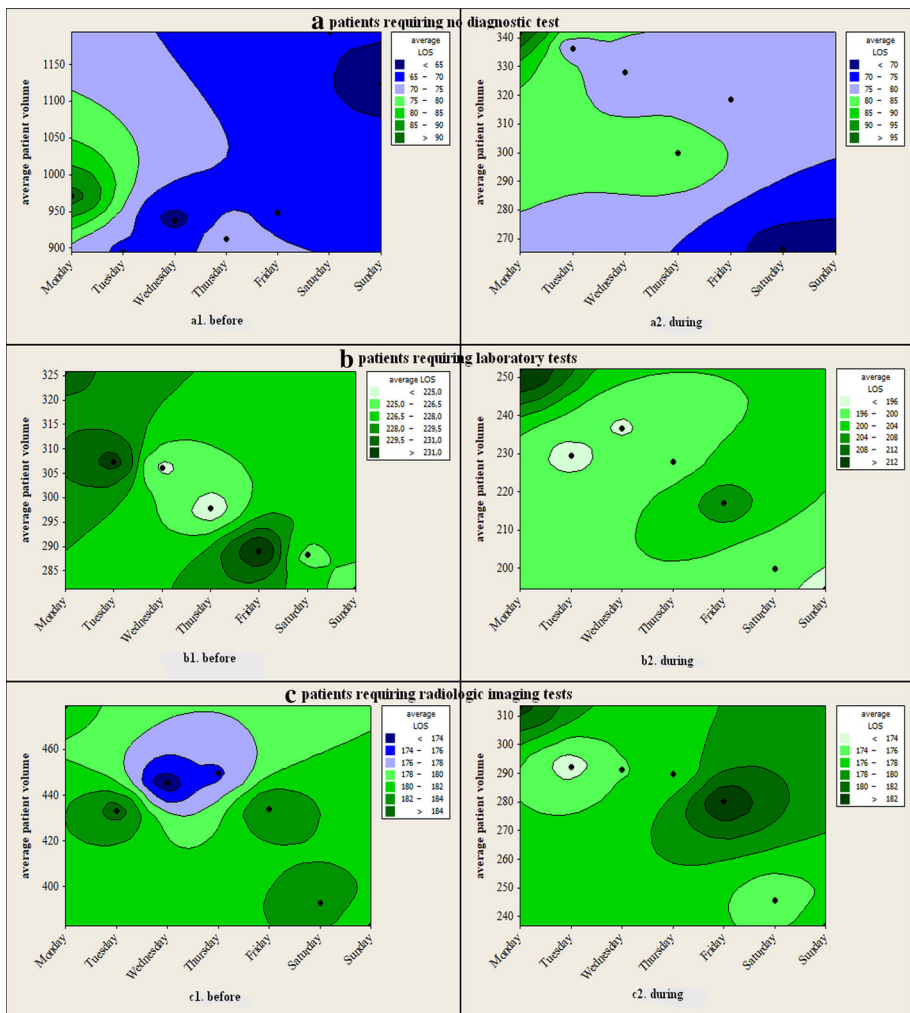

Fig. 4 Daily average patient numbers and LOS values for each day of the week

decreased levels were observed in the average LOS values of patients requiring diagnostic tests during the pandemic period. This could be due to the decreases in resource utilization. When resource utilization decreases, it accelerates access to resources and enables more efficient use. Based on the daily distributions of patient numbers, one other finding should be noted. In the patients requiring no diagnostic test category, while Saturdays and Sundays, that is, the weekend, had the highest daily patient numbers compared to weekdays in the before-COVID-19 period, daily numbers were the highest on Mondays in the during-COVID-19 period. The impact of government restrictions and prohibitions on ED operations is directly seen in this finding. Since most of the weekends, total curfews were imposed during this period, patient volume, particularly in the patients requiring no diagnostic test category, sharply decreased at weekends.

Table 2 shows the total number of patients arriving at this ED based on the categories of the considered demographics (gender, age, triage, arrival types, diagnosis) for the before- and during-COVID-19 study periods comparatively.

From the values of Table 2, it should be seen that the distribution of patient numbers based on gender changed in the during-COVID-19 period compared to the before-COVID-19 period, as the number of male patients increased. Differences were also depicted based on age distributions. For each of the three categories, in the young group, age:[0–14], patient numbers and distributions sharply decreased in the during-COVID-19 period, and in the elderly group, age ≥ 65. In contrast, distributions fell in the patients requiring diagnostic tests category overall. There was some increase in this age category. Additionally, for all three types, the distribution of patients arriving by ambulance increased in the during-COVID-19 study period. Another important finding showed that, while distributions of green zone patients significantly decreased in the patients requiring no diagnostic test category, the distribution of green zone patients increased in some other categories. Finally, significant differences were observed between 22 different ICD-10 encoded diagnosis types on the distributions of the four main groups. These ICD-10 codes were J00-J99 (disease of the respiratory system), M00-M99 (disease of musculoskeletal system and connective tissue), R00-R99 (symptoms, signs, and abnormal clinical and laboratory findings, not elsewhere classified), and U00-U85 (codes for special purposes, COVID-19 here). The significant differences in the distributions of these diagnosis types are associated with the COVID-19 pandemic and the season.

5.2 Model results

The proposed model was implemented in the obtained data sets of the corresponding case study. Since we focus on four primary ED operations, the model was tested repetitively four times for Operations 1 through 4, which increased the model's validity.

In this section, the relation between the identified input variables and the corresponding output variables for each ED operation of interest will be presented based on the results of the Pearson correlation analysis. The statistical association between the model variables is presented in a heat-map structure in the Appendix for each operation. In Table 3, we showed the direction, magnitude, and significance level of the relationships, notably the significant input variables of the model for each operation.

From the values of Table 3, it is observed that the defined input variables of Operation 1, X1 through X5, were all significantly related to the output variable Y1. Besides, the relations were in a negative direction. This demonstrates how policy-based restrictions and prohibitions reduce the predicted number of daily patients in the during-COVID-19 period. Nonetheless, while it is observed that the system dynamics related to input variable X1 had a

Table 2 Distributions of each patient demographic variable for three categories in the before- and during-COVID-19 periods

Variable	Levels	Patients requiring no diagnostic test		Patients requiring laboratory tests		Patients requiring radiology tests	
		Before	During	Before	During	Before	During
		n (%)	n (%)	n (%)	n (%)	n (%)	n (%)
Gender	Female	47,670 (47.742)	14,784 (42.444)	16,636 (55.540)	12,407 (49.324)	21,894 (51.177)	14,899 (47.316)
	Male	52,179 (52.258)	20,048 (57.556)	13,317 (44.460)	12,747 (50.676)	20,887 (48.823)	16,589 (52.684)
Age	age: [0–14]	20,722 (20.753)	3,683 (10.574)	4,726 (15.778)	1,715 (6.818)	7,991 (18.679)	2,951 (9.372)
	age: (15–64)	70,980 (71.087)	27,538 (79.059)	17,730 (59.193)	18,310 (72.792)	26,814 (62.677)	23,309 (74.025)
	age ≥ 65	8,147 (8.159)	3,611 (10.367)	7,497 (25.029)	5,129 (20.390)	7,976 (18.644)	5,228 (16.603)
Triage level	green room	68,335 (68.438)	12,122 (34.801)	2,624 (8.760)	6,490 (25.801)	7,746 (18.106)	7,279 (23.117)
	yellow room	23,212 (23.247)	14,888 (42.742)	20,542 (68.581)	12,037 (47.853)	21,406 (50.036)	12,280 (38.999)
	red room	2,313 (2.316)	2,076 (5.960)	5,904 (19.711)	5,737 (22.808)	4,833 (11.297)	4,950 (15.720)
	trauma room	5,989 (5.998)	4,904 (14.079)	883 (2.948)	890 (3.538)	8,796 (20.561)	6,979 (22.164)
Arrival type	walk in	98,553 (98.702)	33,148 (95.165)	24,508 (81.822)	19,224 (76.425)	37,374 (87.361)	25,642 (81.434)
	by ambulance	1,296 (1.298)	1,684 (4.835)	5,445 (18.178)	5,930 (23.575)	5,407 (12.639)	5,846 (18.566)
ICD-10 encoded diagnosis	A00-B99	3,095 (3.100)	755 (2.168)	241 (0.805)	193 (0.767)	156 (0.365)	96 (0.305)
	C00-D49	32 (0.032)	24 (0.069)	49 (0.164)	31 (0.123)	43 (0.101)	24 (0.076)
	D50-D89	135 (0.135)	139 (0.399)	75 (0.250)	88 (0.350)	37 (0.086)	51 (0.162)
	E00-E89	108 (0.108)	122 (0.350)	131 (0.437)	117 (0.465)	74 (0.173)	81 (0.257)
	F01-F99	696 (0.697)	515 (1.479)	223 (0.744)	183 (0.728)	132 (0.309)	124 (0.394)
	G00-G99	1,211 (1.213)	540 (1.550)	335 (1.118)	221 (0.879)	415 (0.970)	277 (0.880)
	H00-H59	646 (0.647)	453 (1.301)	10 (0.033)	7 (0.028)	12 (0.028)	6 (0.019)

Table 2 (continued)

Variable	Levels	Patients requiring no diagnostic test		Patients requiring laboratory tests		Patients requiring radiology tests	
		Before n (%)	During n (%)	Before n (%)	During n (%)	Before n (%)	During n (%)
	H60-H95	1,541 (1.543)	576 (1.654)	61 (0.204)	36 (0.143)	63 (0.147)	46 (0.146)
	I00-I99	1,113 (1.115)	730 (2.096)	1,192 (3.980)	857 (3.407)	959 (2.242)	715 (2.271)
	J00-J99	36,073 (36.128)	5,368 (15.411)	3,174 (10.597)	5,223 (20.764)	4,427 (10.348)	4,913 (15.603)
	K00-K95	3,925 (3.931)	1,789 (5.136)	1,580 (5.275)	935 (3.717)	1,184 (2.768)	753 (2.391)
	L00-L99	1,384 (1.386)	1,154 (3.313)	69 (0.230)	67 (0.266)	38 (0.089)	47 (0.149)
	M00-M99	13,190 (13.210)	7,625 (21.891)	2,459 (8.210)	1,933 (7.685)	14,039 (32.816)	8,924 (28.341)
	N00-N99	2,050 (2.053)	1,206 (3.462)	2,434 (8.126)	1,562 (6.210)	1,673 (3.911)	1,195 (3.795)
	O00-O9A	28 (0.028)	25 (0.072)	17 (0.057)	18 (0.072)	54 (0.126)	28 (0.089)
	P00-P96	49 (0.049)	51 (0.146)	50 (0.167)	39 (0.155)	5 (0.012)	4 (0.013)
	Q00-Q99	3 (0.003)	5 (0.014)	4 (0.013)	5 (0.020)	5 (0.012)	6 (0.019)
	R00-R99	11,797 (11.815)	3,544 (10.175)	13,110 (43.769)	7,599 (30.210)	12,321 (28.800)	6,957 (22.094)
	S00-T88	2,556 (2.560)	1,790 (5.139)	193 (0.644)	179 (0.712)	632 (1.477)	537 (1.705)
	U00-U85	0 (0.000)	644 (1.849)	0 (0.000)	2,106 (8.372)	0 (0.000)	1,971 (6.260)
	V00-Y99	1,448 (1.450)	1,286 (3.692)	517 (1.726)	426 (1.694)	1,509 (3.527)	801 (2.544)
	Z00-Z99	18,769 (18.797)	6,491 (18.635)	4,029 (13.451)	3,329 (13.234)	5,003 (11.694)	3,932 (12.487)

significant relation with the model output variable, the relations of the policy-based variables, particularly X5, X2, and X3, were more substantial. However, for Operation 2, we observed that most of the selected input variables were not significantly related to Y2. We observed that only X1-fcast and X5 were related considerably to Y2. As also seen in Table 3, most of the selected input variables of the model were significant while modeling Operations 3 and 4. We also observed that some of the selected policy-based variables had significant negative relations with Y3 and Y4. This result demonstrated that such policies caused substantial decreases in resource usage of EDs during-COVID-19 period.

After analyzing the effects of the identified input variables on the operations, we further processed the obtained data sets using the MLP neural networks. MLPRegressor in the neural network package of the *sklearn* module in Python was initialized to process the data sets of the models. The solver function of the algorithm chosen was *adam()* and the activation function

Table 3 Correlation results for significant input parameters of the model for each of the operations

Modeling daily patient numbers: Operation 1	Modeling average daily LOS: Operation 2	Modeling daily numbers of ordered laboratory tests: Operation 3	Modeling daily numbers of ordered radiologic imaging tests: Operation 4
$r_{Y1-X1} = -0.25^{**}$	$r_{Y2-X1-fcast} = 0.18^{*}$	$r_{Y3-X1-fcast} = 0.39^{**}$	$r_{Y4-X1-fcast} = 0.87^{**}$
$r_{Y1-X2} = -0.40^{**}$	$r_{Y2-X5} = -0.29^{**}$	$r_{Y3-X2} = -0.36^{**}$	$r_{Y1-X2} = -0.42^{**}$
$r_{Y1-X3} = -0.43^{**}$		$r_{Y3-X38} = 0.24^{**}$	$r_{Y1-X3} = -0.31^{**}$
$r_{Y1-X4} = -0.22^{*}$		$r_{Y3-X39} = 0.33^{**}$	$r_{Y1-X5} = -0.66^{**}$
$r_{Y1-X5} = -0.76^{**}$		$r_{Y3-X40} = 0.19^{*}$	$r_{Y1-X70} = 0.34^{**}$
		$r_{Y3-X41} = 0.27^{**}$	$r_{Y1-X71} = 0.36^{**}$
		$r_{Y3-X43} = 0.29^{**}$	$r_{Y1-X72} = 0.42^{**}$
		$r_{Y3-X46} = 0.33^{**}$	$r_{Y1-X73} = 0.38^{**}$
		$r_{Y3-X49} = 0.28^{**}$	$r_{Y1-X74} = 0.30^{**}$
		$r_{Y3-X51} = 0.39^{**}$	$r_{Y1-X75} = 0.42^{**}$
		$r_{Y3-X53} = 0.19^{*}$	$r_{Y1-X77} = 0.26^{**}$
		$r_{Y3-X55} = -0.28^{**}$	$r_{Y1-X78} = 0.40^{**}$
		$r_{Y3-X58} = 0.37^{**}$	$r_{Y1-X79} = 0.32^{**}$
		$r_{Y3-X59} = 0.22$	$r_{Y1-X80} = 0.28^{**}$
		$r_{Y3-X62} = -0.24^{**}$	$r_{Y1-X82} = 0.32^{**}$
		$r_{Y3-X63} = -0.28^{**}$	$r_{Y1-X83} = 0.30^{**}$
		$r_{Y3-X64} = -0.38^{**}$	$r_{Y1-X87} = 0.25^{**}$
		$r_{Y3-X66} = 0.27^{**}$	$r_{Y1-X88} = 0.19^{*}$
		$r_{Y3-X67} = 0.39^{**}$	$r_{Y1-X90} = 0.36^{**}$
			$r_{Y1-X91} = 0.32^{**}$
			$r_{Y1-X92} = -0.30^{**}$
			$r_{Y1-X93} = 0.37^{**}$
			$r_{Y1-X95} = -0.20^{*}$
			$r_{Y1-X98} = 0.30^{**}$
			$r_{Y1-X99} = 0.24^{**}$

*Correlation is significant in 95%CI
**Correlation is significant in 99%CI

selected was *relu()*. The train test split was used for experimentation, and the separation was applied randomly. The train/test split value of 0.8 was applied. The experiment was repeated several times to obtain the optimal model parameters for learning rate, momentum, and the number of hidden layers. The prediction performances of the models were tested on the test data sets based on the mean absolute percentage error (MAPE), and the root mean square error (RMSE) statistics. The optimal model parameters specific to each model and model performances are represented in Table 4.

Table 4 shows that the proposed model performs well for managing ED operations in the COVID-19 periods. The model, tested in four different operations, achieved around 90% accuracy in two of these operations and 95% accuracy in one. On the other hand, in one of the

Table 4 MLP neural network performances on ED operations predictions during-COVID-19

ED operations during-COVID-19 and related model	Optimized parameters (learning rate-LR, momentum-M, number of hidden layers-HL	Model performance	
		MAPE	RMSE
Modelling daily patient numbers: Operation 1	LR = 0.01, M = 0.01, HL = 2	10.573	88.624
Modelling daily average LOS: Operation 2	LR = 0.5, M = 0.2, HL = 3	19.309	40.473
Modelling daily numbers of ordered laboratory tests: Operation 3	LR = 0.001, M = 0.125, HL = 4	9.884	28.325
Modelling daily numbers of ordered radiologic imaging tests: Operation 4	LR = 0.019, M = 0.19, HL = 3	5.924	20.324

operations modeling average daily LOS, the model performance was lower, having around 80% accuracy. The model results are also consistent with the findings on the relationship between model attributes. Since lower relations were observed between variables on LOS modeling, prediction performance could not achieve the modeling performances on other operations with higher correlation levels between the variables. Nonetheless, the achieved accuracies were still acceptable and practically implementable compared with related studies and targeted levels.

6 Discussion

This study emphasizes implementing emerging technologies, particularly BDA, in managing health services' operations. As noted in the literature (Akter & Wamba, 2019; Donthu & Gustaffson, 2020), we believe that the challenges posed by COVID-19 can be tackled using these technologies. Grounded in dynamic capabilities and the related context of BDAC, we proposed a model for the management of ED operations in emergencies. To show the validity of the proposed model, we tested it in four different primary operations of EDs. While defining the model variables, besides using the system dynamics-related factors, we implemented additional variables to represent the effect of government restrictions and prohibitions imposed to cope with emergencies. Thus, we contribute to the literature by proposing an efficient system for managing ED operations in emergencies by implementing emerging BDA technologies and investigating the effects of these policy-based factors on ED operations.

The model has been validated using real-life data from a large-scale ED operating in İzmir city, Turkey. Although the overcrowded environments of EDs are a global problem, this problem is worse in some countries, such as Turkey, in which EDs are frequently occupied unnecessarily by non-emergent patients. By comparing the daily and total patient volumes in the before- and during-COVID-19 study periods, the descriptive findings on the case data set mainly represent the significance of this problem in this ED since patient volumes sharply decreased during-COVID-19 period. By classifying patients into three categories—patients requiring no diagnostic tests, laboratory tests, and radiologic imaging tests—and identifying that the reduction in patient volume was mainly caused by the first category (patients requiring no diagnostic tests), we also provide evidence to support this finding. We additionally support this finding by observing increases in the average LOS values of patients who do not

require any diagnostic tests. Contrarily, the average LOS values were observed to decrease for patients requiring diagnostic tests during-COVID-19 period. All these findings demonstrate that most patients make unnecessary visits to this ED. This result supports the existing studies reporting a substantial decrease in ED visits during the COVID-19 (Jeffery et al., 2020; Schereyer et al., 2020). We also contribute to the literature by linking this result to one of the biggest operational challenges of EDs and demonstrating that unnecessary visits are the leading cause of overcrowded ED environments. Besides, from the practical viewpoint, the decrease in patient numbers and diagnostic test orders during COVID-19 may be used for hospital managers' better scheduling and allocation of ED resources. Although a sharp decline was observed in these values, a significant increase was observed in patients' average LOS values, meaning that arriving patients to EDs during-COVID-19 required more and longer interventions and treatments. Thus, better planning and allocation of ED resources will be essential for functioning these services during emergencies.

Significant decreases in patient volume during-COVID-19 period may be related to two main factors. First, the pandemic created stress in patients. To protect themselves from being infected, they may have avoided visiting EDs if they did not have emergent or urgent situations. Second, due to the government restrictions and prohibitions imposed, people were partially obliged to stay at home if they did not need an emergent or urgent health service. Since the first factor is more behavioral, it is beyond the scope of this study. However, we aimed to identify the impacts of policy-based factors on ED operations by adopting our model into a case study representing the overcrowding of ED environments and frequently unnecessary ED visits. This result supports the existing studies reporting decreased patient volumes due to the governmental actions taken in fighting COVID-19 (Kendzerska et al., 2021; Sözen et al., 2022). It also enhances literature by considering this effect in developing prediction models for patient volumes, average stay lengths of patients, and resource utilization of EDs during this pandemic period.

The depicted decreases in the average LOS values of patients requiring laboratory or radiologic imaging tests in the during-COVID-19 period compared to the before-COVID-19 period highlights another essential finding of this study. While this finding has been widely presented in the literature (Houshyar et al., 2020; Jeffery et al., 2020), by proposing an efficient data-driven model for predicting the daily utilization of these services during this pandemic, once again, this study differs from the existing studies. As an interpretation, it should be noted that the decrease in the utilization of EDs' resources accelerates the access to resources and enables more efficient use of them, and solves another challenge of long waiting times in EDs.

A critical step in devising the proposed model was determining the model inputs appropriately. In the case study implementation, input variables are defined in two categories as (i) variables representing system dynamics and (ii) government restrictions and prohibitions. While policy-based variables are defined commonly in implementing the proposed model for considered ED operations, system dynamics-based variables are explicitly defined for each operation. The primary demographics, such as gender, age, triage level, arrival type, and ICD-10 encoded diagnosis in the ED patients' database, were used and appropriately transformed to identify operation-specific input variables. The values of these variables were measured based on the data set for the before-COVID-19 study period.

After forming data sets in this manner, the proposed model was tested for the considered ED operations of managing the daily number of patients, average daily LOS, daily numbers of laboratory tests ordered, and daily numbers of radiologic imaging tests ordered. When the relations between the specified input variables and the daily number of patients during-COVID-19 period were analyzed, it was concluded that policy-based attributes have more

significant effects on the daily number of patients compared to the identified system dynamics-related input variables. Some relations were observed between the defined input variables, such as transport bans and restrictions on the elderly, and the daily average LOS during-COVID-19. While policy-based variables, such as total curfew, are related to the daily number of laboratory tests ordered during-COVID-19 period, some other system dynamics-related input variables also have relations with the corresponding output variable. Finally, both policy-based attributes, namely, curfews and restrictions and transport bans, and most system dynamics-related variables seemed to relate to the daily number of radiologic imaging tests ordered. It is also noted that the depicted correlations between policy-based input variables and the corresponding output variables had negative signs showing that such policies may decrease patient volume and the utilization of primary ED resources. From these findings, it is concluded that the restrictions and prohibitions imposed by the government in coping with COVID-19 have had significant impacts on the management of ED operations. This result is in line with the existing studies (Akter & Wamba, 2019; Haldane & Morgan, 2021; Sözen et al., 2022). Our findings contribute to the literature by investigating the effects of system dynamics-related and government-imposed actions together and comparatively for different operations of EDs.

The obtained data sets were then used to implement the proposed model in the four primary ED operations using MLP neural networks. Neural network algorithms have been presented in the literature for automatic COVID-19 detection (Qayyum et al., 2021) and infection rate predictions (Wieczorek et al., 2020; Sozen, Sariyer & Ataman, 2021). By implementing this algorithm in multi real-life operations of EDs, the used contexts of this BDA technique have been extended in this paper. The model has high prediction accuracies for managing daily patient numbers and daily use of resources during a pandemic. Besides achieving or exceeding the prediction performances of models in the literature in this context (Whitt & Zhang, 2019), these results achieved the targeted value (85%) set by this ED's service providers. Although the model's performance is lower in predicting daily average LOS values, it can still match the performance of previous studies (Ataman & Sariyer, 2021) and achieve the targeted value of 75% accuracy. This operation's targeted value is smaller than others since modeling LOS is more complex. Thus, with the proposed model, which utilizes BDA, we believe that even the most challenging health services operations may be managed efficiently, and the difficulties posed by emergencies can be handled.

7 Implications

7.1 Theoretical implications

The study underpins the dynamic capability theory in two folds. The emergencies are featured with the rapidly changing conditions and parameters. Hence, the data inherent in the crises exhibits a dynamic feature. Eventually, the properties of the data set are subject to change. Therefore, DC theory arises as an ideal theoretical structure to embrace dynamically changing environments caused by emergencies. While such situations cause rapid changes in patient volumes, varieties, and characteristics, from different viewpoints, the government's policies, such as restrictions and prohibitions in fighting these situations, create additional modifications in the system environment. For instance, during emergencies caused by pandemic illnesses, volumes of infected patients may significantly increase. The total patient volume in health services may also be decreased due to panic and stress factors created by being

infected and based on governmental policies such as stay-home warnings and curfews. All of this support how emergencies create dynamically changing environments. This implication is strengthened by comparing the main features of the health system data before-COVID19 and during-COVID19 periods. Hence, the study's findings state that DC is applicable in emergencies.

The second fold of the theoretical implication can be asserted that dynamically changing environments caused by emergencies affect decision-making processes. As the properties of the data set act in a dynamic manner, it forces the decision-making process to be in line with this rapid change. Even though the big data nature of the data sets stays the same, the time pressure on the decision-makers is higher due to the fast and dynamic change of data. Thus, the need for rapid decision-making increases the need for the capabilities related to data analytics. Therefore, BDAC is a crucial structure for building the decision-making mechanism within emergencies. Once again, the study's findings support this implication by highlighting the significant changes in patient volumes, demographics (such as distributions on gender, age, triage, arrival type, and diagnosis categories), and diagnostic test requirements (resource usage) between the before and during pandemic periods. Being aware of changes in such parameters and having capabilities of shaping ED services rapidly in response to these changes provide significant advantages in fighting emergencies. Thus, it can be depicted that BDAC is applicable in emergencies.

Thus, although dynamic capability theory and the recent view of BDAC have been well presented in management literature, this study attempts to extend their usage in the health context, particularly under emergencies. By discussing the rapidly changing parameters and features of the health system environments in emergencies, proposing a model highlighting a need for BDAC, and implementing this model in a real-life big data study, this study aims to contribute to the context of these theories.

7.2 Managerial implications

Our main suggestion is that the decision-makers of health services have BDAC and use big data sets of their system environments effectively to create meaningful knowledge, which should then be turned rapidly into actions. Adopting the system to dynamically changing conditions caused by emergencies quickly and efficiently should be achieved by taking advantage of the emerging technologies and by being able to implement these technologies in practice for planning and managing operations. Based on the results of this study, we showed how the current emergency, COVID-19, and the government policies change the patient volumes, varieties, and characteristics. Since such changes may significantly affect ED operations, and because it is essential to provide rapid responses to these changing situations, it should also be noted that understanding and identifying the main factors that impact their operations is critical. Suppose system-related factors are characterized and appropriately measured, and external factors that may arise from the emergencies are carefully followed and identified. All these factors can be collectively used in modeling ED operations by taking advantage of BDA technologies. Hence, the system may function efficiently even in emergencies. The challenges arising in the ED environment and posed by emergencies can be easily managed in such conditions. Based on such models, the managers will be able to make rapid and correct decisions and adapt the system efficiently to dynamically changing conditions.

We also highlight the importance of data recording in health services. Although BDA and BDAC are significant technologies and capabilities for health services and particularly emergency departments, all these do not make any sense if there exist no data sets to analyze, create

knowledge, and use in decision making. Therefore, we suggest that the ED decision-makers focus on electronic recording and data storage processes and should not avoid investing in these processes and systems. Since the quantity and quality of the data allow meaningful and actionable knowledge, the decision-makers should spend time and effort testing the quality of recording processes. Assuring the existence of valid and reliable big data sets is the primary prior condition for an ED decision-maker to take advantage of BDA in fighting against the challenges and uncertainties posed by emergencies. This is also very important for satisfying the sustainable monitoring in ED processes and real-time emergency response applications.

7.3 Policy implications

This study mainly emphasized the overcrowded ED environments and the significance of this problem in our ED, even regularly. Based on the findings, we noted that this overcrowding might be primarily associated with the redundant use of these services, particularly for patients who occupy them for non-urgent situations. These types of patients generally perceive EDs as gateways to hospitals. To not make an appointment and wait in line for polyclinic services or receive a health service at weekends or nights, as EDs provide a 7/24 service, patients may choose to visit EDs. However, providing a timely and efficient service becomes more challenging in these crowded environments based on limited resources. If ED operations cannot be appropriately managed, patients even in emergent and urgent situations may have to wait to be treated, which may have significant consequences. To cope with this overcrowding problem, different government actions should be taken.

This study also analyzes the effects of government restrictions and prohibitions in coping with emergencies, particularly COVID-19. It should be highlighted that imposing these policies is crucial in emergencies to protect the functioning of EDs. Government policies, such as curfews (lock-downs), transport bans, and partial restrictions on the elderly or the young, may decrease patient volumes, redundant ED visits, and resource utilization.

In today's era that requires awareness of big data and the related contexts of BDA and BDAC, we also advise policymakers to invest in data storage and analysis in government agencies. Governments must create awareness of these emerging concepts and technologies in public institutions. Governments should pay time, effort, and budget to regularly control the agencies based on their data storage capabilities, qualities, quantities, and reliabilities. It may be necessary to impose sanctions on institutions deficient in these concepts during these controls. Creating high-quality, reliable, and robust data sets in government institutions will improve more accurate and timely decision-making processes in emergency and routine situations. This may also help governments integrate sustainability orientation in health care operations and flexibility for managing emergencies.

8 Conclusion

While emergencies precisely demonstrate dynamically changing environments, health services are the main actors in coping with those situations. Governments are another leading actor; they are the enablers of the system and may impose restrictions and prohibitions to protect the functioning of health services. We, therefore, propose a model, which is grounded in the dynamic capabilities and related context of BDAC, for managing operations of one of the most crucial health services units, namely, EDs, during emergencies. With this model, we aim not only to manage ED operations sustainably but also to investigate the effects

of imposed restrictions and prohibitions on these operations. Besides proposing a generic machine learning integrated model for managing ED operations under emergencies and validating this model for different operations of EDs, taking the governmental actions as the main factors of this model and thus showing how they affect these operations is the main contribution of this paper. This study also contributes to dynamic capability theory and BDAC by extending their usage for the decision-making processes of one of the most important actors of health services, EDs, under emergencies. We also believe that the proposed BDA-driven model or more general big data and BDA implementations in real-life operations may help satisfy sustainable operations in EDs.

The proposed model adopts one of the most popular BDA techniques: multilayer perceptron neural networks. The model is implemented in a real-life data set representing a large-scale ED with daily patient volumes of more than 1,000. The current COVID-19 pandemic represents a focused emergency. The model is validated in four different primary operations of EDs: managing daily numbers of patients, daily average stays of patients and daily usage of resources (laboratory services and radiologic imaging services). The prediction performance of the proposed model varies between 80 to 95% for the corresponding operations. This study also showed that policy-based factors might significantly affect ED operations. Such restrictions and prohibitions may cause sharp decreases in patient volumes and resource utilisations in EDs, which are challenged by overcrowding. Thus, imposing such policies is crucial to protect ED functioning in emergencies.

The main limitation of this study was that its experimental evaluation was based on data collected from a single case study, and its findings may, therefore, not generalize to emergency departments with significantly different patient populations, characteristics, volumes, and varieties. Generalizing these results to other emergency departments with different operational processes, guidelines, and dynamics may also be impossible. Operationally, to ensure robustness, it is critical to check for variations in patient and system dynamics patterns observed in this case study to transfer the proposed model to other emergency departments. Future studies should include a broader set of operations, measurements, internal and external variables, and outcomes from multiple emergency departments to support the robustness of the proposed model. Finally, we expect that the implementation of deep learning techniques can potentially further improve the predictive performance of the proposed model for considered operations of EDs.

Appendix 1

Correlation matrices of the identified variables of the models for corresponding ED operations.
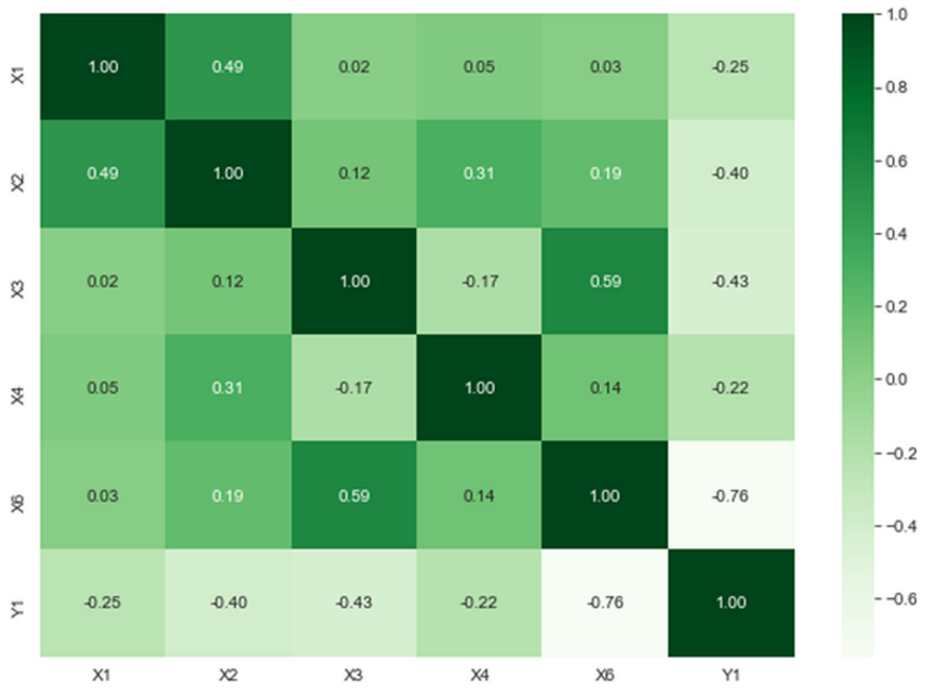
See Fig. 5.

Fig. 5 Operation 1: Modelling daily numbers of ED patients during COVID-19
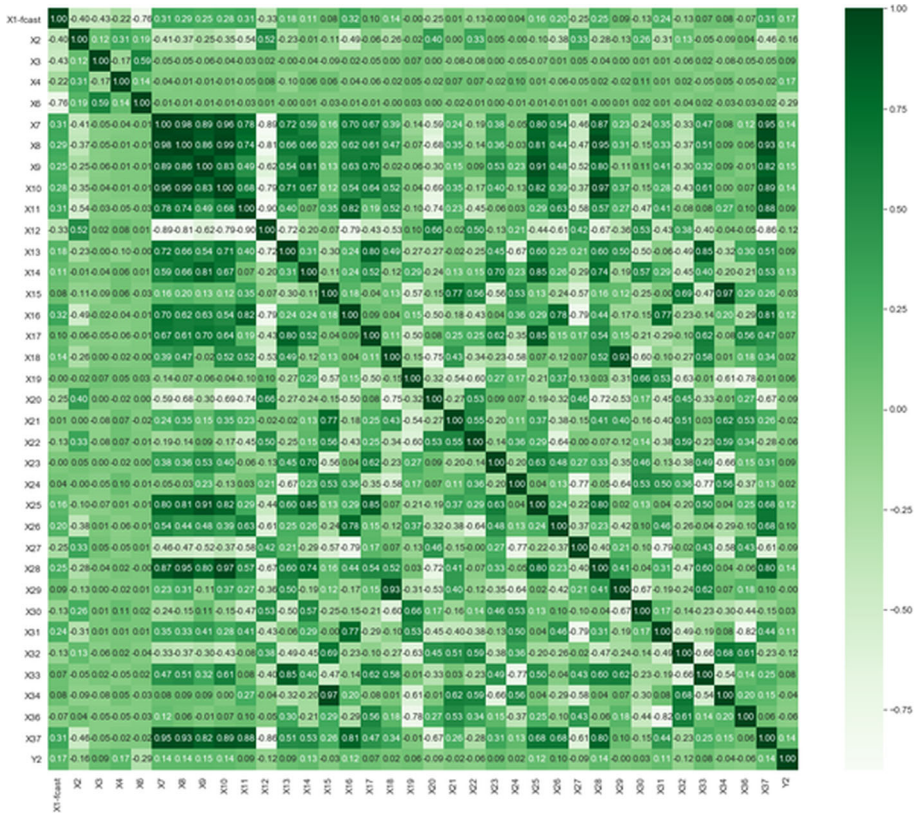
Appendix 2

See Fig. 6.

Fig. 6 Operation 2: Modelling daily average LOS of ED patients during COVID-19
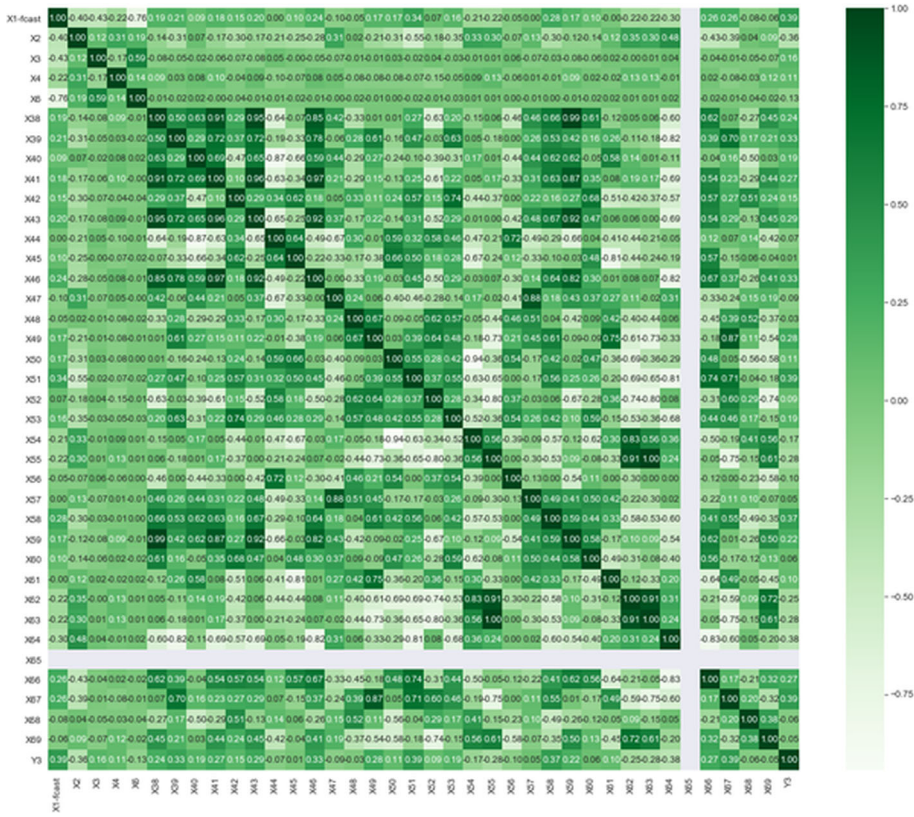
Appendix 3

See Fig. 7.

Fig. 7 Operation 3: Modelling daily numbers of laboratory tests ordered
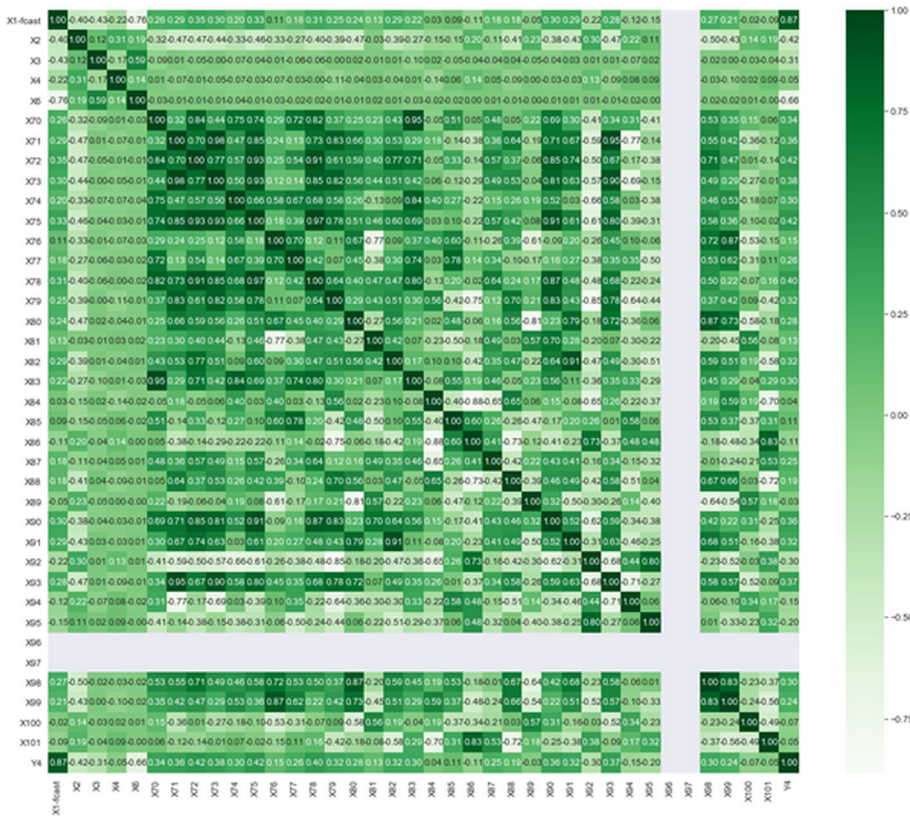
Appendix 4

See Fig. 8.

Fig. 8 Operation 4: Modelling daily numbers of radiologic imaging tests ordered

References

Abdel-Basset, M., Chang, V., & Nabeeh, N. A. (2021). An intelligent framework using disruptive technologies for COVID-19 analysis. *Technological Forecasting and Social Change, 163*, 120431.

Akter, S., & Wamba, S. F. (2019). Big data and disaster management: A systematic review and agenda for future research. *Annals of Operations Research, 283*(1), 939–959.

Alinaghian, M., & Goli, A. (2017). Location, allocation and routing of temporary health centers in rural areas in crisis, solved by improved harmony search algorithm. *International Journal of Computational Intelligence Systems, 10*(1), 894–913.

Ataman, M. G., & Sarıyer, G. (2021). Predicting waiting and treatment times in emergency departments using ordinal logistic regression models. *The American Journal of Emergency Medicine, 46*, 45–50.

Bag, S., Gupta, S., Choi, T. M., & Kumar, A. (2021). Roles of innovation leadership on using big data analytics to establish resilient healthcare supply chains to combat the COVID-19 pandemic: A multimethodological study. *IEEE Transactions on Engineering Management*. https://doi.org/10.1109/TEM.2021.3101590

Birkinshaw, J., Zimmermann, A., & Raisch, S. (2016). How do firms adapt to discontinuous change? Bridging the dynamic capabilities and ambidexterity perspectives. *California Management Review, 58*(4), 36–58.

Choi, T. M. (2021). Fighting against COVID-19: What operations research can help and the sense-and-respond framework. *Annals of Operations Research*. https://doi.org/10.1007/s10479-021-03973-w

Choi, T. M., Wallace, S. W., & Wang, Y. (2018). Big data analytics in operations management. *Production and Operations Management, 27*(10), 1868–1883.

Das, S. K., Pervin, M., Roy, S. K., & Weber, G. W. (2021). Multi-objective solid transportation-location problem with variable carbon emission in inventory management: A hybrid approach. *Annals of Operations Research*. https://doi.org/10.1007/s10479-020-03809-z

Deloitte. (2020). *COVID-19: Managing supply chain risk and disruption*. Retrieved November 10, 2020, from https://www2.deloitte.com/global/en/pages/risk/articles/covid-19-managing-supply-chain-risk-anddisruption.html.

Donthu, N., & Gustafsson, A. (2020). Effects of COVID-19 on business and research. *Journal of Business Research, 117*, 284.

Feng, Q., & Shanthikumar, J. G. (2018). How research in production and operations management may evolve in the era of big data. *Production and Operations Management, 27*(9), 1670–1684.

Fortune. (2020). *94% of the Fortune 1000 are seeing coronavirus supply chain disruptions: Report*. Retrieved November 10, 2020, from https://fortune.com/2020/02/21/fortune-1000-coronavirus-china-supply-chain-impact/.

Goli, A., Zare, H. K., Tavakkoli-Moghaddam, R., & Sadeghieh, A. (2019). Hybrid artificial intelligence and robust optimization for a multi-objective product portfolio problem Case study: The dairy products industry. *Computers and Industrial Engineering, 137*, 106090.

Goli, A., Khademi-Zare, H., Tavakkoli-Moghaddam, R., Sadeghieh, A., Sasanian, M., & Malekalipour Kordestanizadeh, R. (2021). An integrated approach based on artificial intelligence and novel meta-heuristic algorithms to predict demand for dairy products: a case study. *Network Computation in Neural Systems, 32*(1), 1–35.

Guo, M., Zhang, Q., Liao, X., Chen, F. Y., & Zeng, D. D. (2020). A hybrid machine learning framework for analyzing human decision-making through learning preferences. *Omega, 101*, 102263.

Gupta, S., Justy, T., Kamboj, S., Kumar, A., & Kristoffersen, E. (2021). Big data and firm marketing performance: Findings from knowledge-based view. *Technological Forecasting and Social Change, 171*, 120986.

Haldane, V., & Morgan, G. T. (2021). From resilient to transilient health systems: The deep transformation of health systems in response to the COVID-19 pandemic. *Health Policy and Planning, 36*(1), 134–135.

Harvard Business Review. (2020). *Coronavirus is proving we need more resilient supply chains*. Retrieved November 5, 2020, from https://hbr.org/2020/03/coronavirus-is-proving-that-we-need-moreresilient-supply-chains.

Hossain, M. K., Thakur, V., & Mangla, S. K. (2021). Modeling the emergency healthcare supply chains: Responding to the COVID-19 pandemic. *Journal of Business and Industrial Marketing*. https://doi.org/10.1108/JBIM-07-2020-0315

Houshyar, R., Tran-Harding, K., Glavis-Bloom, J., Nguyenat, M., Mongan, J., Chahine, C., Loehfelm, T. W., Kohli, M. D., Zaragoza, E. J., Murphy, P. M., & Kampalath, R. (2020). Effect of shelter-in-place on emergency department radiology volumes during the COVID-19 pandemic. *Emergency radiology, 27*(6), 781–784.

Huang, H., Peng, Z., Wu, H., & Xie, Q. (2020). A big data analysis on the five dimensions of emergency management information in the early stage of COVID-19 in China. *Journal of Chinese Governance, 5*(2), 213–233.

Jeffery, M. M., D'onofrio, G., Paek, H., Platts-Mills, T. F., Soares, W. E., Hoppe, J. A., Genes, N., Nath, B., & Melnick, E. R. (2020). Trends in emergency department visits and hospital admissions in health care systems in 5 states in the first months of the COVID-19 pandemic in the US. *JAMA internal medicine, 180*(10), 1328–1333.

Kapoor, K., Bigdeli, A. Z., Dwivedi, Y. K., & Raman, R. (2021). How is COVID-19 altering the manufacturing landscape? A literature review of imminent challenges and management interventions. *Annals of Operations Research*. https://doi.org/10.1007/s10479-021-04397-2

Kendzerska, T., Zhu, D. T., Gershon, A. S., Edwards, J. D., Peixoto, C., Robillard, R., & Kendall, C. E. (2021). The effects of the health system response to the COVID-19 pandemic on chronic disease management: A narrative review. *Risk Management and Healthcare Policy, 14*, 575.

Kumar, A., Shankar, R., Choudhary, A., & Thakur, L. S. (2016). A big data MapReduce framework for fault diagnosis in cloud-based manufacturing. *International Journal of Production Research, 54*(23), 7060–7073.

Kumar, A., Shankar, R., & Aljohani, N. R. (2020). A big data driven framework for demand-driven forecasting with effects of marketing-mix variables. *Industrial Marketing Management, 90*, 493–507.

Lee, S. M., & Trimi, S. (2021). Convergence innovation in the digital age and in the COVID-19 pandemic crisis. *Journal of Business Research, 123*, 14–22.

Marić, J., Galera-Zarco, C., & Opazo-Basáez, M. (2021). The emergent role of digital technologies in the context of humanitarian supply chains: A systematic literature review. *Annals of Operations Research*. https://doi.org/10.1007/s10479-021-04079-z

Midya, S., Roy, S. K., & Yu, V. F. (2021). Intuitionistic fuzzy multi-stage multi-objective fixed-charge solid transportation problem in a green supply chain. *International Journal of Machine Learning and Cybernetics, 12*(3), 699–717.

Mishra, D., Gunasekaran, A., Papadopoulos, T., & Childe, S. J. (2018). Big Data and supply chain management: A review and bibliometric analysis. *Annals of Operations Research, 270*(1), 313–336.

Mondal, A., & Roy, S. K. (2021). Multi-objective sustainable opened-and closed-loop supply chain under mixed uncertainty during COVID-19 pandemic situation. *Computers & Industrial Engineering, 159*, 107453.

Mondal, A., & Roy, S. K. (2022). Application of Choquet integral in interval type-2 Pythagorean fuzzy sustainable supply chain management under risk. *International Journal of Intelligent Systems, 37*(1), 217–263.

Papadopoulos, T., Baltas, K. N., & Balta, M. E. (2020). The use of digital technologies by small and medium enterprises during COVID-19: Implications for theory and practice. *International Journal of Information Management, 55*, 102192.

Sarkis, J. (2021). Supply chain sustainability: Learning from the COVID-19 pandemic. *International Journal of Operations & Production Management, 41*(1), 63–73.

Schreyer, K. E., Daniel, A., King, L. L., Blome, A., DeAngelis, M., Stauffer, K., Desrochers, K., Donahue, W., Politarhos, N., Raab, C., & McNamara, R. (2020). Emergency department management of the Covid-19 pandemic. *The Journal of emergency medicine, 59*(6), 946–951.

Thakur, V., Mangla, S. K., & Tiwari, B. (2021). Managing healthcare waste for sustainable environmental development: A hybrid decision approach. *Business Strategy and the Environment, 30*(1), 357–373.

Tirkolaee, E. B., Goli, A., Ghasemi, P., & Goodarzian, F. (2022). Designing a sustainable closed-loop supply chain network of face masks during the COVID-19 pandemic: Pareto-based algorithms. *Journal of Cleaner Production, 333*, 130056.

Qayyum, A., Razzak, I., Tanveer, M., & Kumar, A. (2021). Depth-wise dense neural network for automatic COVID19 infection detection and diagnosis. *Annals of Operations Research*. https://doi.org/10.1007/s10479-021-04154-5

Queiroz, M. M., Ivanov, D., Dolgui, A., & Wamba, S. F. (2020). Impacts of epidemic outbreaks on supply chains: Mapping a research agenda amid the COVID-19 pandemic through a structured literature review. *Annals of Operations Research*. https://doi.org/10.1007/s10479-020-03685-7

Sanders, N. R., & Ganeshan, R. (2018). Big data in supply chain management. *Production and Operations Management, 27*(10), 1745–1748.

Sarıyer, G., & Ataman, M. G. (2020). The likelihood of requiring a diagnostic test: Classifying emergency department patients with logistic regression. *Health Information Management Journal, 51*(1), 13–22.

Sarıyer, G., Ataman, M. G., & Kızıloğlu, İ. (2020). Analyzing main and interaction effects of length of stay determinants in emergency departments. *International Journal of Health Policy and Management, 9*(5), 198–205.

Sözen, M. E., Sarıyer, G., & Ataman, M. G. (2022). Big data analytics and COVID-19: Investigating the relationship between government policies and cases in Poland, Turkey, and South Korea. *Health Policy and Planning, 37*(1), 100–111.

Sharma, M., Luthra, S., Joshi, S., & Kumar, A. (2020). Developing a framework for enhancing survivability of sustainable supply chains during and post-COVID-19 pandemic. *International Journal of Logistics Research and Applications, 25*(4–5), 433–453.

Rubbio, I., Bruccoleri, M., Pietrosi, A., & Ragonese, B. (2020). Digital health technology enhances resilient behaviour: Evidence from the ward. *International Journal of Operations and Production Management, 40*(1), 34–67.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509–533.

Teece, D., Peteraf, M., & Leih, S. (2016). Dynamic capabilities and organizational agility: Risk, uncertainty, and strategy in the innovation economy. *California Management Review, 58*(4), 13–35.

Verma, S., & Gustafsson, A. (2020). Investigating the emerging COVID-19 research trends in the field of business and management: A bibliometric analysis approach. *Journal of Business Research, 118*, 253–261.

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research, 70*, 356–365.

Whitt, W., & Zhang, X. (2019). Forecasting arrivals and occupancy levels in an emergency department. *Operations Research for Health Care, 21*, 1–18.

Wieczorek, M., Siłka, J., & Woźniak, M. (2020). Neural network powered COVID-19 spread forecasting model. *Chaos, Solitons & Fractals, 140*, 110203.

Yu, W., Zhao, G., Liu, Q., & Song, Y. (2021). Role of big data analytics capability in developing integrated hospital supply chains and operational flexibility: An organizational information processing theory perspective. *Technological Forecasting and Social Change, 163*, 120417.

Zollo, M., & Winter, S. G. (2002). Deliberate learning and the evolution of dynamic capabilities. *Organization Science, 13*(3), 339–351.