# A Data Envelopment Analysis-based Approach for Managing Performance of Public Service Systems During a Disaster

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**ABSTRACT**

In addition to their normal task of supporting community participation, engagement, and improved information access, information technology-based public service systems are also essential for maintaining critical services and providing effective communication with citizens before, during, and after emergencies. This study focuses on the impacts of disaster events on the operational performance of such service systems and discusses opportunities for managing service efficiency by rearranging and reallocating resources during emergencies. To the best of our knowledge, this is the first attempt to provide a practical method for improving the relative efficiency of public service systems in such a context. We suggest a Data Envelopment Analysis (DEA) approach for quantifying the relative efficiencies associated with service requests from an input-output-based standpoint, and discuss the Orange County (Florida) 311 non-emergency service system, in the context of the COVID-19 pandemic, as an example of how such operational efficiency can be managed during a disruption.

**Keywords**

Performance measurement, Efficiency, Data Envelopment Analysis, 311, Public Service.

## INTRODUCTION

A strong motivation behind embracing the concept of 'smart cities' is the desire to benefit from enriched participatory action and engagement that can help create more livable, connected, and sustainable communities (Kalkanci, Rahmani, & Toktay, 2019). Governments actively develop e-government practices that offer many benefits such as easy and timely access, more useful information, and high-quality interactions between stakeholders (Yang, Kim, Nam, & Lee, 2004; Axelsson, Melin, & Lindgren, 2013). Recently, smart technologies implemented by governments have gained further attention in terms of their ability to maintain critical services and communicate with citizens before, during, and after an emergency (Pamukcu & Zobel, 2021).

This study focuses on 311 non-emergency service systems, which provide a good example of e-government services that not only need to sustain their ongoing functionality but also often need to adapt that functionality in response to additional needs that arise during a crisis. 311 service systems are considered part of the smart city movement (Zobel, Baghersad, & Zhang, 2017), and they were initially created to eliminate the high numbers of non-emergency calls being received by 911 emergency systems (Schwester, Carrizales, & Holzer, 2009). Although these systems focus on non-emergency service requests, there often is still a need to respond to them quickly. Managing such a system therefore often requires triaging the calls and prioritizing them based on their urgency, in order to more effectively respond to different types of community need. Such systems support timely information exchange and build mutual trust between the government and the public, which allows municipalities to provide more effective and efficient disaster management by leveraging inputs from both groups. (O'Brien, 2016; Pamukcu, Zobel, & Ge, 2021).

In this context, government organizations have the opportunity to monitor and evaluate their operational performance and thus to improve service provision in future emergencies (Baghersad, Zobel, & Behara, 2020). Considering the associated uncertainties and resource limitations, as well as the changing service needs of people in a crisis environment, governmental service systems often must not only maintain critical services but also add additional functionality to better respond to an emergency. The effectiveness of such systems at doing so can be assessed by considering the concept of service efficiency, which provides a good measure of performance subject to resource limitations. Since one would expect citizen needs during a crisis to vary across different groups and different locations, capturing and addressing this variability is important for improving overall performance.

With these needs in mind, this study proposes the following research questions:

*RQ1: What are the impacts of a disaster event on the service efficiency of an information technology-based public service system?*

*RQ2: What are the main challenges of maintaining the efficiency of a public service delivery provision in a coordinated system environment during a disaster?*

We seek to answer these questions by expanding on the previous research on the use of 311 non-emergency call systems for supporting local emergency management efforts, and by focusing, in particular, on the performance of the 311 system in Orange County, Florida during the COVID-19 pandemic.

Our overall objective is to provide a practical approach for assessing the success of an information technology-based community service system at employing new crisis-related initiatives, and to uncover opportunities for maintaining the associated service efficiency during emergencies. We therefore introduce a Data Envelopment Analysis (DEA) approach for measuring the relative efficiencies associated with different service requests. This is done from an input-output-based standpoint that extends previously proposed approaches for assessing the efficiency of service systems.

To the best of our knowledge, this research effort is the first attempt to quantify the relative service efficiencies of a public service system, with respect to requests received from different technology channels and different physical neighborhoods. As such, it is intended to provide government agencies with an effective means of enhancing their service system operations management, and addressing possible inequalities, by supporting the more efficient use of available service capacity. In addition, we aim to open room for further discussion about the potential for digital and service inequalities across communities and to uncover additional opportunities to clarify the factors that can lead to disparity in service delivery.

The remainder of the paper is structured as follows: First, we provide background information about the functioning of 311 non-emergency service systems, as well as information about their use in disaster situations. We then discuss public service efficiency as a measure of service system performance. This is followed by the proposed Data Envelopment Analysis approach and the description of the problem context and the dataset. Finally, we conclude the paper by discussing how the relative efficiency quantification approach can help with effectively managing operational efficiency during a disastrous event, and we provide several future research directions.

## 311 Non-emergency Service Systems

Community call service systems are good examples of governmental information and communication technology implementations that promote coproduction by bringing government bodies and residents together to collaborate on maintaining the public's well-being (O'Brien, 2016). 311 service systems are specific examples of such systems that were originally created to eliminate the need for processing high numbers of non-emergency calls within existing 911 emergency systems (Schwester et al., 2009). A 311 system is a coordinated information technology-based community service system that unites non-emergency service requests from multiple jurisdictions, thus allowing citizens to easily request a non-emergency service without needing to know the responsible agency. Although 311 systems were originally designed as simple call-center-based services, over time they have turned into multimedia hubs, municipal data sources, and community engagement tools (Samuel, 2019). 311 services are currently available in many cities in the United States and Canada, and they usually support streamlining call intake by providing more automated contact options such as integrated voice response (IVR) technology, automated texting, web chat, and app-driven requesting options.

Even though 311 systems are focused on handling calls for non-emergency service needs, these requests are still relevant during a crisis situation. In other words, even if a call itself doesn't require an immediate emergency response, it may still be related to longer-term critical issues that arise in a crisis. For this reason, 311 systems typically need to handle significant changes in non-emergency information and service needs during disasters (Zobel et al., 2017; Baghersad et al., 2020; Zobel, 2021; Pamukcu et al., 2021). For example, as a result of the COVID-19 outbreak, many 311 systems experienced sudden peaks in complaint volumes after announcements of a State of Local Emergency. These systems thus had to boost their capacities to handle the vast number of calls of citizens seeking help during the emergency (Sanders, 2020). In a recent study, Pamukcu and Zobel (2021) demonstrate the New York City 311 service system's reactions to the COVID-19 pandemic, in particular, and show that 311 call data can be used to reflect variations in public responses to a severe health crisis, emphasizing the potential for enhancing service performance before, during, and after emergencies.

Beyond new service needs that actively arise during a disaster, 311 systems are also helpful for collecting information about, or reporting on, various critical issues related to all phases of a crisis. Examples include requesting information about shelter availability, evacuation routes, or road closures in disaster preparation; reporting a power outage, damaged property, or flooding in disaster response; and requesting debris collection, reporting a tree blocking road or hazardous material risk in recovery from the disastrous outcomes. A good example of this is the use of the Orange County 311 system to collect post-hurricane services requests during the 2004 hurricane season, when four consecutive hurricanes severely hit the Orlando metropolitan area. Since then, the local government of Orange County, Florida has encouraged its citizens to report any future disaster-related problems to the 311 Service Center (Williams, 2011; Kennedy, 2015).

In response to the COVID-19 crisis, Orange County 311 (OC311) introduced new options under the *Public Safety* category to answer citizens' questions about various coronavirus aid and funding opportunities, COVID-19 testing, or vaccines. Also, OC311 processed citizen reports for incidents of businesses failing to comply with CDC guidelines and Emergency Executive Orders related to public gatherings and social distancing. Similarly, New York City asked citizens to report COVID-19 related issues such as social distancing and face-covering violations through their 311 system, in order to increase the City's situational awareness and to collect timely information to react more quickly (Pamukcu & Zobel, 2021). Such initiatives ultimately support providing more reliable and timely information to the public and increase the effectiveness of the City's response, thus making the system an important tool for disaster management (Pamukcu et al., 2021).

Access to digital and traditional communication tools can be restricted in disaster situations due to disruption of infrastructures and services. In particular, disasters disproportionately affect different population groups and disadvantaged communities are generally more vulnerable to the impacts of such events. If socioeconomic factors restrict access to certain communication channels, this can then reduce access to community services during emergencies. Although 311 non-emergency call systems typically provide citizens with a range of call-based and web-based contact methods, there is a chance that limited access to some communication channels might lead to unequal access to public services and, therefore, to service inequality during a disaster. Accordingly, service providers should be aware of differences in neighborhoods' service request behaviors, and their choices of contact methods, particularly during a crisis, in order to ensure that they are providing equitable service among requests from different communities and across different channels.

### Public Service Efficiency

Disaster operations management requires methods that support quick and efficient decision-making processes to improve preparedness, speed, and the use of limited resources (Altay & Green, 2006). It is essential to realize that when a disaster occurs, numerous problems arise that must be solved in order to reestablish the normal functioning of the community and its systems. Uncertainties in disaster events, including their timing, severity, and impacts, increase the complexity of such problems and necessitate effective, efficient, and equitable emergency management. Public services are among the systems directly affected by disasters, and since they have already established high-quality communication and engagement between people and their local governments, they play a crucial role in collecting and assessing the information and service needs of affected populations. These systems need to be resilient to such events to be able to continue their critical functions, and it is important for them to try to maintain a reasonable level of efficiency in providing their services even when it is necessary to reallocate resources and extend available system capacities to do so.

In this particular study, we operationalize efficiency as the performance indicator of a public service system that is prone to disruptions in its normal functioning due to a disaster. We consider service efficiency, from an input-output perspective, as the cost of producing a given outcome (Andrews & Entwistle, 2010) representing the best possible allocation of resources given a set of limitations on increasing output levels (Korhonen & Syrjänen, 2004). We develop a relative efficiency model for the coordinated 311 service system using a Data Envelopment Analysis approach, by defining decision-making units (DMUs) as the requests received from different neighborhoods via different technology channels on each day of the week.

For the sake of simplicity, we first assume that the system uses a fixed capacity for responding to service requests, measured as the personnel-hours available given the staffing capacity and working hours for each day of a week. Many such systems will potentially have emergency plans that allow them to use extra resources to address the increased needs of impacted populations during crises. These additional resources will be limited, however, due to physical limitations such as working space, time, or trained personnel. We will thus discuss the opportunity to reallocate shared resources among multiple access channels to maintain target service efficiency despite disruptions in service provision. Assuming that there is no notion of differential quality for completed service requests, we consider the number of resolved requests in a day and the average resolution time of requests as the outputs of interest in the 311 service system. We further consider the number of daily service requests as the uncontrollable input and we consider the staffing level as the controllable input of this system.

There are multiple potential advantages of continually monitoring the service provision efficiency of coordinated community service systems. First, a coordinated system with multiple actors brings diverse efficiency levels, enabling possible improvements by benchmarking and efficiently allocating shared resources. Second, monitoring the changing efficiency levels of everyday operations allows identifying significant changes in performance due to disruptions and, therefore, brings the potential to move towards a more resilient system in terms of efficiency. Third, improved efficiency enables improved speed and volume in service provision. This is even more critical during emergencies when normal functioning of regular services should continue at the same time that service providers handle increased numbers of newly raised public needs. Last, but not least, monitoring the performance of a coordinated system enables effective cooperation between all stakeholders of the system by strengthening mutual trust, effective communication, and shared decision-making.

## METHODOLOGY

### Data Envelopment Analysis

Data envelopment analysis (DEA), originally developed by Charnes et al. (1978), is a nonparametric modeling method that estimates the relative efficiency of a particular decision-making unit (DMU) within a group of DMUs. DEA can control large numbers of variables and relations using mathematical programming techniques and it consumes multiple inputs to produce multiple outputs (Cooper, Seiford, & Zhu, 2011).

A simple relative efficiency model of Charnes et al. (1978) measures the relative efficiency of $n$ independent DMUs, with each consuming $m$ inputs to produce $s$ outputs. Given the input and output vectors of $DMU_d(d = 1, \dots, n)$ are denoted as $Xj = (x_{1j}, \dots, x_{mj})$ and $Yj = (y_{1j}, \dots, y_{sj})$, respectively; the basic DEA model can be formulated as follows:

$$e_d = Max \frac{\sum_{r=1}^{s} \mu_r y_{rd}}{\sum_{i=1}^{m} \omega_i x_{id}}$$

$$s.t. \quad \frac{\sum_{r=1}^{s} \mu_r y_{rd}}{\sum_{i=1}^{m} \omega_i x_{id}} \leq 1 \qquad j = 1, \dots, n$$

$$\mu_r, \omega_i \geq 0 \qquad r = 1, \dots, s\,; i = 1, \dots, m$$

In the above model, $e_d$ is the relative efficiency of $DMU_d$, $\mu_r$ and $\omega_i$ are unknown relative weights of $r^{th}$ output and $i^{th}$ input, respectively. Model determines a set of optimal relative weights for each $DMU_d(d = 1, \dots, n)$, by maximizing its ratio of aggregated outputs to aggregated inputs while ensuring assigning a unique efficiency ratio $e_d$ to each $DMU_d(d = 1, \dots, n)$.

The DEA method has been used extensively in operations performance evaluations, and its accuracy has been proven in many public and private sectors. Some examples are health care (Bahadori et al., 2016; Dimas et al., 2012), education (Haelermans & Ruggiero, 2013), banking (Bhatia & Mahendru, 2016; Puri & Yadav, 2013), supply chains (Azadi et al., 2014), and transportation systems (Daraio et al., 2016; von Hirschhausen & Cullmann, 2010), among others. For a further detailed list of examples, readers can visit an extensive review of DEA-related articles by Emrouznejad and Yang (2018), including theory and methodology developments since 1978. Although DEA is still considered a new approach in disaster analysis and management, a number of studies also have applied DEA for performance evaluation in this context. Wei et al. (2004), for example, proposed a DEA-related method to evaluate the relative severity of the impacts of natural disasters on different regions. Li et al. (2013) and Saharizan et al. (2018) also used the DEA method to estimate the spatial regions' relative vulnerability to flooding. Klumpp et al. (2021) address the lack of in-depth efficiency research in humanitarian operations and present a boot-strapped DEA window analysis to assess humanitarian logistics efficiency concerning multiple actor levels and time series requirements. DEA has also been used in the performance evaluation of government emergency management services. The assessment of fire protection performance using DEA is one of these examples (Choi, 2005; Peng, Song, Guohui, Sen, & Heping, 2014). While Choi (2005) conducted a DEA analysis of fire and emergency services of Florida, Peng et al. (2014) use an international perspective to evaluate the relative fire protection performance of different countries.

The validity of the DEA approach in call center performance measurement has also been proven in the literature. Ducic et al. (2020) use the DEA to compare the relative efficiency of multiple contact centers of a single company to maintain customer satisfaction and the company's overall efficiency. Additionally, Poykayil Jayananda Panicker (2002) evaluates the performance of customer service representatives in a call center using DEA. Our problem context differs from these studies by including a time component to account for the change in efficiency over time and assessing the performance of a coordinated call center responsible for connecting customers with multiple service agencies.

None of these existing studies assess the relative service performance of information technology-based public service systems that need to persist during a disaster and help with local disaster management operations. The DEA approach is well suited for this because it allows for minimizing deviation from target service performance by modeling the reutilization of available resources during emergencies. Demonstrating this capability is very important from a broader disaster management perspective because it can be generalized across other systems such as public transportation, logistics, and healthcare, as well as to other community services that face operational disruptions.

DEA implementations in the literature vary based on a system's organizational structure. For example, Li et al. (2019) propose a model for a decentralized system that determines maximal efficiency scores across all DMUs by minimizing the total deviation through the integration of a goal programming method with the DEA approach. Many others have proposed a centralized DEA approach for coordinated organizational settings where the decision-maker seeks a collective goal rather than individual interests, and a resource allocation scheme is defined according to a collective objective (Fang, 2017; Fang & Li, 2015; Lozano, Villa, & Brännlund, 2009; Lozano, Villa, & Canca, 2011). Our study also focuses on a coordinated service system, where decisions made in coordination with multiple business partners and fixed resources should be efficiently allocated to multiple DMUs based on agreed-upon standards, and including specific system characteristics and constraints.

### Empirical Data Set: Orange County Florida 311

Our empirical study focuses on Orange County, Florida's 311 system. Orange County 311 (OC311) is a well-established non-emergency service system that was initially created in 2002 as a pilot program. Since then, OC311 has been enabling Orange County residents to get help or information about local municipal services (Pamukcu et al., 2021). OC311 integrates various information and communication technologies (ICTs) into its system, such as multiple phone and internet-based access modes, multiple language options, and additional alternative options for people with disabilities, in order to connect with a broadest possible range of individuals in the population. Service requests are initially received and processed by OC311 and then they are distributed to the various agency partners within Orange County in order to fulfill requests other than simple information requests.

We were able to get access to the complete dataset of OC311 system service requests for 2017-2021, along with the daily staffing levels and operating hours in the main 311 service center, thanks to an ongoing partnership with the East Central Florida Regional Planning Council (ECFRP) and the Orange County government. This OC311 service request data includes a pre-determined list of attributes for each entry, including the exact time of the service request, a detailed description of the incident category, the resolution status, the priority of the complaint, the contact method, and the incident coordinates, among others. A detailed list of the available attributes is provided by Pamukcu et al. (2021).

In combination with the 311 dataset, the historical staffing levels and working hours will allow us to quantify the daily staffing capacity and the corresponding levels of service efficiency. Based on the daily call volumes, the response times for each request, and the average staffing capacity of the OC311 for each day of the week, we propose the relative efficiency model explained in detail in the following sections. Given this proposed model, we will then compare the relative service efficiency before and during the emergency.

### Quantifying the Service Efficiency of OC311

As indicated above, this study proposes a DEA model to calculate the relative service efficiencies of 311 requests from varying intake channels in different neighborhoods of Orange County, Florida. DEA will be used as a performance monitoring tool to compare and analyze service efficiency for each DMU before and after the COVID-19 pandemic. For simplicity and to ensure a fair comparison among DMUs we only focus on information-seeking requests, which are generally resolved within a day. We differentiate between the requests by considering their pre-assigned priority levels, in order to account for their relative criticality. In this way, we control requests' criticality since a vast majority of information-seeking calls have the same priority label in the OC311 system. Furthermore, since the service capacity of each work-day differs depending on the pre-defined working hours and staffing levels (See Figure 1), we also control for the day of the week.

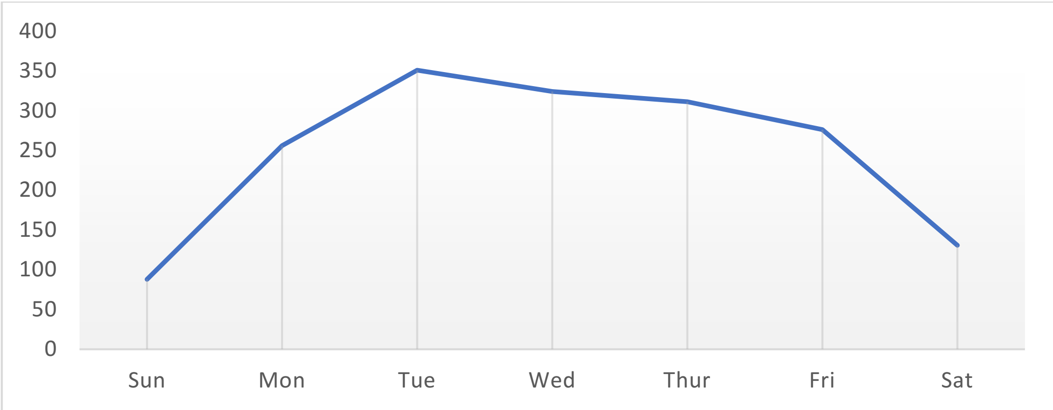


**Figure 1. Orange County 311 – Strategic Service Capacity (from June 1st, 2020 through May 28th, 2021)**

Our decision-making units (DMUs) will be based on three categories: (1) *contact type*, (2) *neighborhood (jurisdiction)*, and (3) *day-of-week* (with County Holidays accounted for). The detailed list of elements for each category is provided in Table 1.

*The* average *number of requests* is the uncontrollable input of the model, and the *service capacity* is the controllable input of this model, where the service capacity can be calculated by multiplying the average daily staffing level times the working hours on the corresponding day of the week. The *number of resolved requests within a day* (i.e., 24 hours) and the *average resolution time* are defined as the system's outputs, where the resolution time of each incident can be simply calculated by subtracting incident creation time from incident closure time.

**Table 1. Orange County 311 – Selected categories for DEA analysis and detailed list of elements**

| | |
|---|---|
| **Day-of-Week** | Sunday, Monday, Tuesday, Wednesday, Thursday, Friday, Saturday |
| **Contact type** | Chat, Email, Mobile App, Online Requests, Phone, Voicemail |
| **Jurisdiction** | Apopka, Bay Lake, Belle Isle, Eatonville, Edgewood, Lake Buena Vista, Maitland, Oakland, Ocoee, Orlando, Unincorporated, Windermere, Winter Garden, Winter Park |

Given these input and output parameters, we can formulate the efficiency measure of a specific DMU as follows:

$$Efficiency\ score_d = \frac{\mu_1(\#\ of\ resolved\ requests\ within\ a\ day)_d + \mu_2(average\ resolution\ time)_d}{\omega_1(service\ capacity)_d + \ \omega_2(daily\ \#\ of\ requests)_d}$$

*Proposed DEA Model*

We can now apply the DEA model to measure the relative efficiency of the different DMUs.

Given a set of *n* independent DMUs, with each consuming *m* inputs to produce *s* outputs at time interval *t*, the input and output vectors of $DMU_{dt}$ (d=1,…,n; t=1,…,k) are denoted as $Xjt = (x_{1jt}, \dots, x_{mjt})$ and $Yjt = (y_{1jt}, \dots, y_{sjt})$, respectively. Time interval *t* denotes a specific time period over which the efficiency is calculated based on $Xjt$ and $Yjt$. The proposed output-oriented linear model, adapted from Banker, Charnes and Cooper (1984), is then as follows:

$$e_{dt} = Max \sum_{r=1}^{s} \hat{\mu}_r y_{rdt} + c_{dt}$$

$$s.t. \sum_{i=1}^{m} \widehat{\omega}_i x_{idt} = 1$$

$$\sum_{r=1}^{s} \hat{\mu}_r y_{rjt} - \sum_{i=1}^{m} \widehat{\omega}_i x_{ijt} + c_{dt} \leq 0 \quad j = 1, \dots, n$$

$$\hat{\mu}_r, \widehat{\omega}_i \geq 0 \quad r = 1, \dots, s\,; i = 1, \dots, m \tag{3}$$

In this linear model, $e_{dt} \in [0,1]$ is the relative efficiency assigned to $DMU_{dt}$. The additional constant variable $c_{dt}$ in the objective function allows variable returns to scale. $\mu_r$ and $\omega_i$ are the unknown relative weights of the $r^{th}$ output and the $i^{th}$ input, respectively, and the model optimizes estimates of these values for each $DMU_{dt}$ in order to maximize the system's efficiency. The complete DEA solves $n \times k$ linear programs, one for each DMU at each time interval.

Solving this set of linear programs will allow us to build an efficient frontier from the relative efficiency scores of the different DMUs; this will allow us to identify the set of inefficient DMUs. Given the updated daily staffing capacities during both normal time and disaster mode, the DEA model will identify relative inefficiencies in the system during crisis and non-crisis time intervals. The results of non-crisis times will be compared with the updated efficiency scores during the disaster period, where the system experiences significant changes in uncontrollable input of daily number of service requests. In this way, we will be able to compare and analyze the deviations in individual efficiency scores as well as the change in the system's overall efficiency. Having access to this information will allow the city to reevaluate its operational performance during a disaster to better prepare for future emergencies. The governments might already be managing such disasters well with their current emergency plans. However, there is always a real possibility that future crises might bring new challenges and complexities (the COVID-19 pandemic is an unfortunate example of this), and resource management will always be a crucial part of disaster operations management. This practical approach will help the city examine if there is room for improving service performance by reutilizing available resources among multiple operational units to provide efficient and equitable service to all service seekers.

## CONCLUSION

This study emphasizes the importance of resource planning to maintain systems functioning during disasters. In the context of the Orange County 311 system, each incoming request needs to be processed by a human operator so staffing level and daily working hours determine the service capacity of the system. Although the system allows incident entry via multiple intake channels, each request is triaged and processed by trained 311 operators carefully before directing the request to the responsible agency. The efficiency in the 311 system thus affects the overall service performance of the systems' business partners. For this reason, cooperative emergency plans and coordination between partners in crisis mode are crucial for maintaining the efficiency of public service delivery in the collaborative system environment during a disaster.

The findings of the proposed analysis will reveal how significant changes in service demand due to disasters might affect the operational efficiency of a system. Additionally, we argue that there may be a shift in the use of intake channels by communities due to limited access to some technology tools because disasters might disrupt infrastructures and services. Since disasters disproportionately affect different communities, and socio-economically disadvantaged groups are generally more vulnerable to disasters, it may become more difficult for some people to use community service systems. Furthermore, the authorities may lose contact with these vulnerable people who often need the most help in a disaster. Therefore, a shift in use of technology channels during disasters might result in disparities in the service to different communities. The hope is that this research will help uncover opportunities to maintain and even improve target service efficiency and equity across all communities during emergencies by rearranging and reallocating resources and optimizing resource management strategies.

As a future research direction, we plan to extend the proposed approach to address service providers' optimal resource reallocation decisions. Moreover, this study can be complemented by presenting a decision support system to execute the relative efficiency and resource management model for strategic decision-making, especially for crisis times. Such a tool could provide invaluable decision support while a system has been struggling with numerous problems during disasters that must be resolved quickly and efficiently to reestablish system's normal functioning. Another future research opportunity would be extending the relative efficiency model by incorporating a disaster risk factor to account for specific circumstances of disasters that might affect the system capacities and, therefore, the service efficiency. In this way, service agencies could also consider such undesired circumstances based on disaster characteristics and impact while maintaining service performance during the crisis period.

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