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Determinants of Risk Disparity Due to Infrastructure Service Losses in Disasters: A Household Service Gap Model

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The objective of this article is to systematically assess and identify factors affecting risk disparity due to infrastructure service disruptions in extreme weather events. We propose a household service gap model that characterizes societal risks at the household level by examining service disruptions as threats, level of tolerance of households to disruptions as susceptibility, and experienced hardship as an indicator for the realized impacts of risk. The concept of "zone of tolerance" for the service disruptions was encapsulated to account for different capabilities of the households to endure the adverse impacts. The model was tested and validated in the context of power outages through survey data from the residents of Harris County in the aftermath of Hurricane Harvey in 2017. The results show that households' need for utility service, preparedness level, the existence of substitutes, possession of social capital, previous experience with disasters, and risk communication affect the zone of tolerance within which households cope with service outages. In addition, sociodemographic characteristics, such as race and residence type, are shown to influence the zone of tolerance, and hence the level of hardship experienced by the affected households. The results reveal that population subgroups show variations in the tolerance level of service disruptions. The findings highlight the importance of integrating social dimensions into the resilience planning of infrastructure systems. The proposed model and results enable human-centric hazards mitigation and resilience planning to effectively reduce the risk disparity of vulnerable populations to service disruptions in disasters.

KEY WORDS: Community resilience; equitable resilience; infrastructure systems; risk disparity; service gap model; societal risks

1. INTRODUCTION

Occurring with increasing frequency due to climate change, natural hazards pose a threat to the well-being of society due not only to loss of life and property damage, but also to infrastructure service disruptions, which are among the most destructive impacts of the disasters threatening the community resilience (Gall, Borden, Emrich, & Cutter, 2011; Lindell & Prater, 2003). Researchers from various disciplines have focused attention on the assessment of infrastructure services and their underlying interdependencies, and have suggested ways to improve the ability of the built environment to withstand disasters (Gao, Buldyrev, Havlin, & Stanley, 2012; Guidotti et al., 2016; Nateghi, Guikema, & Quiring, 2014; Rasoulkhani & Mostafavi, 2018). The inevitability of natural hazards requires planners to ensure the infrastructures are "safe-to-fail." In other words, it is critical to minimize the consequence of

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the failures (Kim et al., 2017; Park, Seager, Rao, Convertino, & Linkov, 2013) by considering the societal needs and expectations of infrastructure services (Ahern, 2011; Applied Technology Council, 2016).

Based on the current assessment of critical infrastructure, there exists a performance gap between infrastructure system's performance and the public's expectation of these services during the disasters (Applied Technology Council, 2016). It is essential to integrate the needs of the different subpopulations into planning and prioritization of resilient infrastructures (National Institute of Standards and Technology, 2015). One challenge in evaluating this gap is determining how to assess the societal expectations of critical lifelines. Current approaches for designing the lifeline systems assume that all members of the community have equal expectations and needs from infrastructural services and are impacted equally by service disruptions. Disruptions of infrastructure services, however, impose different levels of risk to the well-being of residents, and service disruptions will be experienced differently by different population subgroups (Buckle, Mars, & Smale, 2000; Gamble et al., 2013; Marsh, Parnell, & Joyner, 2010; Peacock, Zandt, Zhang, & Highfield, 2014). Especially vulnerable populations (e.g., old adults, low-income households, and racial minorities) are shown to suffer more from the impacts of infrastructure service disruptions (Baker, 2011; Iversen & Armstrong, 2008; Paton et al., 2006). In this research, the risk disparities are examined in the case of power outages; we propose and test a framework to assess the risk disparities and identify the factors that influence the household's tolerance for the service outages.

There are multiple approaches to incorporate the societal vulnerability of a community in the post-disaster risk disparity analysis. The existing studies have shown that vulnerable population has an uneven capacity for preparedness and lower recovery pace from the negative impacts (Bakkensen, Fox-Lent, Read, & Linkov, 2017). Cutter, Shirley, and Boruff (2003) developed a Social Vulnerability Index (SoVI) to assess the social vulnerability of communities and identified the vulnerable communities based on the socioeconomic and demographic variables. Flanagan et al. (2011) developed a Social Vulnerability Index (SVI) to enable addressing the social perspective in disaster management and reduce the societal impacts of disasters. Other studies such as Cutter, Burton, and Emrich's Baseline Resilience Index for Communities (BRIC) 2010 and Peacock et al.'s Community Disaster Resilience Index (CDRI) 2010 were developed with a common objective of understanding the resilience and vulnerability of communities and address their societal needs in a disaster. While implementing these approaches help to incorporate social characteristics related to households' vulnerability to general disaster threats, they do not provide explanations regarding the mechanisms underlying household-level vulnerability to disruptions in infrastructure services specifically. To address this gap, the focus of this study was to specifically consider household-level susceptibility to services disruptions in understanding the societal risks of infrastructure disruptions.

A number of research studies have focused on the factors that influence the vulnerability of residents to the risks posed by extreme events. Baker (2011) proposed a conceptual framework to assess households' preparedness for power outages in the aftermath of Hurricane Wilma. The study findings show a strong association between the preparedness of households and some demographic characteristic, such as income, age, and race. Lindell and Perry (2000) developed a framework for the assessment of household adjustments to hazards (adjustment defined as residents' preventive actions taken to reduce the risks of disasters). Their findings suggest that the adoption of adjustment practices depends on available resources through their social context and household characteristics. These resources include materials, money, equipment, knowledge and ability, and time and effort; the availability of resources varies among households from different sociodemographic groups. Existing research studies explain the general characteristics of advanced preparedness and resulting adjustment of households during disasters; however, little is known about the effects of infrastructure service disruptions on household well-being. Such understanding should be based on the consideration of societal needs and expectations of the services during the disasters (Clark, Seager, & Chester, 2018; Doorn, Gardoni, & Murphy, 2018; Murphy & Gardoni, 2006; National Institute of Standards and Technology, 2015).

In an effort to address this knowledge gap, Murphy and Gardoni (2008) proposed a novel approach for assessing the tolerance of the public to the potential risks of the disasters. Their study suggested that risks should be evaluated based on the capabilities of individuals, and they proposed the existence of two zones for individual risk tolerance. The first threshold is the minimum acceptable level of attainment of capabilities during disasters. For some households during the hazard, capabilities are temporarily below the minimum acceptable threshold, but individuals are capable of tolerating the threats until the situation reaches their absolute minimum threshold. The second threshold is the absolute minimum attainment of capabilities, a level below which no household should fall. The capability model proposed by Murphy and Gardoni includes a mathematical method for assessing the state of the well-being of individuals based on the acceptable and tolerable zones (Tabandeh, Gardoni, & Murphy, 2018). The proposed model, however, lacks an empirical assessment of the underlying factors affecting the thresholds that characterize the state of well-being. An understanding of these underlying factors is essential for examining the varying capabilities and negative impacts among subpopulations of a community.

One challenge regarding the assessment of the societal needs and expectation is that, in their daily lives, people do not usually experience service outages of long duration; hence, the variation in possible consequences of service disruptions are unknown (Applied Technology Council, 2016). For example, during prolonged power outages, households experience the hardship of the absence of cold food storage, losing food to spoilage, a consequence of the loss of electrical service. An empirical analysis of the determinants of risk disparity due to service disruptions is essential to understanding the effect of adverse impacts of service disruptions among households from different subpopulations. In this article, we propose and empirically examine a conceptual framework for the assessment of household-level risks due to infrastructure service disruptions in disasters. In order to characterize societal risks at the household level, the proposed framework examines service disruptions as threats, level of tolerance of households to disruptions as susceptibility (or vulnerability), and experienced hardship as an indicator for realized impacts of risk. Household service gap framework is developed to answer two fundamental research questions relevant to utility service during severe weather or disaster situations: (1) What are the determinants of risk disparity due to infrastructure service disruptions? and (2) What significant factors affect the tolerance of households from different subpopulations to potential service disruptions? We examined these questions in the context of power outages and utilized empirical data from Hurricane Harvey to test the proposed framework in answering these fundamental research questions.

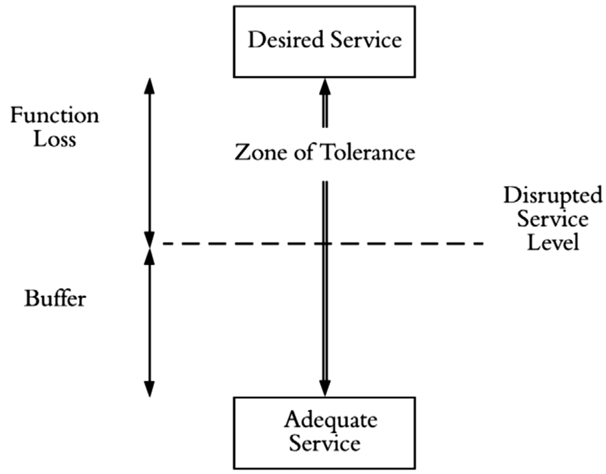

Fig 1. Household service gap model.

2. CONCEPTUAL FRAMEWORK

Societal impacts of infrastructure service disruptions are influenced by a household's exposure to service disruptions (threat), as well as their susceptibility to the threat. The extent to which households are exposed to service disruptions highly affects their experienced hardship. However, households have distinct characteristics and needs from different services and are not equally susceptible to service outages. Considering the unequal susceptibility of households to withstand service disruptions is essential when assessing societal risks at the household level. Therefore, in this study, the concept of the zone of tolerance was developed to characterize the households' susceptibility to service disruptions. We have implemented this framework to investigate the determinants affecting the disparities in the level of tolerance for different households during power outages using empirical data from Harris County in the aftermath of Hurricane Harvey. Household service gap model (Fig. 1) encompasses three main components:

(1) Desired service level: The service level that users expect from infrastructure in a normal situation. In the context of infrastructure services, this level would be equal to the predisaster service function;
(2) Adequate service level: The minimum level of service that a household could

tolerate in a disaster. Different factors could affect the adequate service level for a household, such as sociodemographic factors (McIvor & Paton, 2007; Rasoulkhani, Logasa, Reyes, & Mostafavi, 2018), level of preparedness (Duval & Mulilis, 1999; Miceli, Sotgiu, & Settanni, 2008; Paton, Bajek, Okada, & McIvor, 2010), the hierarchy of needs (Clark et al., 2018), risk perception (Armaş & Avram, 2008; Lindell & Whitney, 2000), capabilities (Gardoni & Murphy, 2013) and access to substitute (Mostafavi, Ganapati, Nazarnia, Pradhananga, & Khanal, 2015); and

(3) Disrupted service level: the service level that users actually receive during disruptions.

2.1. Service Gaps in the Model

Based on these three service levels (desired service, adequate service, and disrupted service), two primary service margins/gaps can be specified:

(1) Zone of tolerance: The difference between desired service level and the adequate service. This gap determines the maximum possible service loss that a household can experience without risk to well-being; and

(2) Buffer/suffer margin: The difference between the disrupted service level and the adequate service level. If the disrupted service level is greater than the adequate service, the buffer would shield a household from risks to well-being. If the disrupted service level is less than the adequate service, a household would experience negative well-being impact; hence, the zone of tolerance is proposed for characterizing households' susceptibility to service disruptions and assessing the risk disparities.

The gaps between service thresholds in the household service gap model and differences in tolerance explain the residents' perceived hardship due to infrastructure service disruptions. For the same level of service disruption, households with a small zone of tolerance perceived a greater level of hardship compared with households with a higher tolerance. The larger the zone of tolerance and the less severe the disruption, the greater the household buffer for service loss, and consequently, the less severe the hardship suffered.

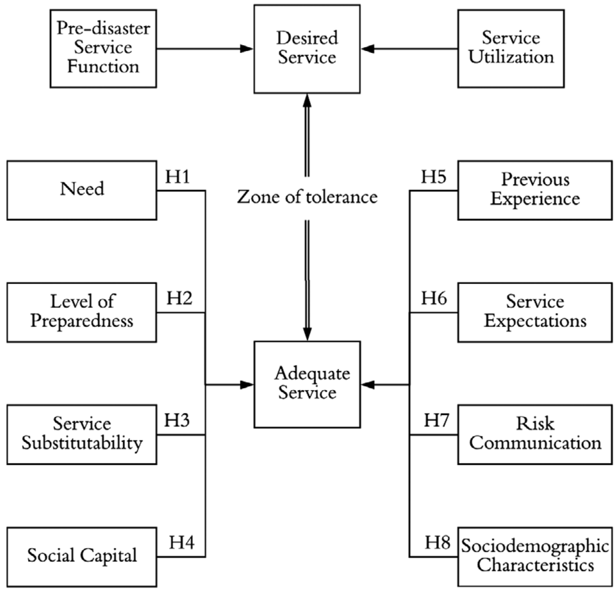

Fig 2. Determinants of the zone of tolerance.

2.2. Factors Influencing the Desired Level of Service

The determinants of the zone of tolerance are shown in Fig. 2. The desired level of service is determined in part by the predisaster service level provided by the infrastructure systems and the household's utilization of the service. When assessing critical infrastructure services, such as electricity and water, the desired level of service may not vary significantly within a specified community. The main reason for the small variance is rooted in the necessity of these utilities. Moreover, the predisaster service condition would not typically vary significantly within a community, though it may change from a community to the others.

Pre-disaster service condition: Residential predisaster experience shapes the level of service people expect in their daily lives. This service level forms a baseline of experience of the service, which can modify the desired level of service (Zeithaml, Berry, & Parasuraman, 1993). A case for the predisaster service level was observed in the aftermath of the Nepal earthquake in 2015 (Nazarnia et al., 2016). A relatively long period of water disruptions limited the resident's access to the water resources; yet the level of the self-reported hardship of the residents in the postdisaster time period was relatively low. The reason for this phenomenon was rooted in the comparative degree of water access in those areas before the earthquake. In areas without water service connection prior to the earthquake, tankers delivered water, so supply was effectively limited to only a few hours per week. Thus, long periods of water disruption was not an onerous issue for the residents of those areas and caused them low hardship (Mostafavi et al., 2015; Zhu, Manandhar, Truong, & Ganapati, 2017). The better the predisaster condition of infrastructure systems, the higher the desired service level by the household (lower disruptions).

Service utilization: The personal needs satisfied by a service influences the desired level of service provision. The less frequently households use the service in their daily life, the lower the desired service level. When a household does not rely on the service in their daily life, it will not suffer from disruptions. For example, the lack of daily internet use can explain the cases in which certain neighborhoods experience no hardship from disruptions in telecommunication services.

2.3. Factors Influencing Adequate Service

The adequate service level, which mainly determines the zone of tolerance for each household, is influenced by the hierarchy of needs, level of preparedness, service substitutability, social capital, previous experience, service expectations, risk communication, and sociodemographic attributes of households.

Hierarchy of needs: The hierarchy of needs, including physical, social, and psychological (National Institute of Standards and Technology, 2015) influences households' expectations of infrastructure services. The household levels of expectation from infrastructure services may vary depending on how a service contributes to meeting the needs of households. Maslow, in his need-hierarchy framework, suggests that more fundamental needs are the prerequisite for higher-order needs (Maslow, 1943). The hierarchy of needs suggests that some needs are more urgent, although all are ultimately necessary for wellbeing (National Institute of Standards and Technology, 2015).

Level of preparedness: A household's preparedness for an upcoming storm also affects its tolerance of service disruption. Preparedness is essential for weathering disruptions during the first 72 hours after an event, as emergency assistance may not be available (Russell, Goltz, & Bourque, 1995). Sociodemographic characteristics are shown to influence the preparedness level of the households (Horney, Snider, Malone, & Cross, 2007; Lindell & Whitney, 2000). Research has also shown that hazard knowledge (Lindell & Whitney, 2000) and disaster-related awareness (Muttarak & Pothisiri, 2012) of the households elevates their preparedness for the events, and formal education can contribute to higher preparedness of households. Some studies have also shown the impact of previous experience of households on the level of preparedness of households (Horney et al., 2007; Russell et al., 1995). The households with previous experience of natural hazards are more likely to have a higher level of preparation actions for an upcoming hazard.

Service substitutability: When services can be substituted, the availability of a substitute would affect the household's zone of tolerance (Zeithaml et al., 1993). Conversely, in the absence of substitutes, and when the need for the service is high, the societal expectation and reliance on infrastructure services are more significant (Applied Technology Council, 2016). Although some substitutes (such as power generators) exist for some services, households may not be aware of their availability or cannot afford them (Baker, 2011). Thus, household characteristics can impact the ability to access substitutes for services during disruptions. In general, households that have the option to satisfy their needs from alternative resources have more tolerance than those who do not.

Social capital: Social capital refers to the resources available in one's social network (Lin, 1999). Social capital provides households with resources to obtain help during extreme events and hence affect ability to tolerate the adverse impacts. Research has shown that affected individuals who have greater social support could better cope with disaster impacts (Aldrich, 2011). The extent of social capital varies between communities, and even among households within a community. This variation is rooted in the personal values of the individuals, community trust, and the inclination of the public to engage in civic duties (Aldrich et al., 2004; Berry & Rickwood, 2000). Hence, the existence of social support could decrease the adequate service level and subsequently increase the zone of tolerance of the households as people with high social capital can rely on the help of others in case of the emergency.

Previous disaster experience: Having a previous experience is shown to affect a household's zone of tolerance for disruptions (Kelley & Davis, 1994; Zeithaml et al., 1993). The disaster literature has also shown that previous disaster experience can lead to better preparedness actions (Horney et al., 2007) and adjustment (Lindell & Hwang, 2008), both of which are considered as protective actions that can increase household tolerance for the potential risks. Having previous experience with disasters has shown to influence the risk perception of the households (Barnett & Breakwell, 2001; Knuth, Kehl, Hulse, & Schmidt, 2014; Lindell & Hwang, 2008), which affects the households' preparedness level and adjustment actions. Prior experiences act as the anchor of reference when people face an upcoming disaster, and the more significant the impacts of the previous experience, the greater the perceived risk from an upcoming event (Applied Technology Council, 2016). With a greater perceived personal risk, people are more likely to adopt more preparedness actions. Thus, previous experiences with disasters could influence a household's zone of tolerance to service disruptions.

Service expectation: Households have an expectation of the restoration of service in the face of disruptions caused by natural hazards. In this case, the greater the expected service, the lower the adequate service and the wider the zone of tolerance (Zeithaml et al., 1993). Households' expectations of subsequent service disruptions vary, and the differences in the individual household's prediction can be affected by their risk perception and communications about service restoration estimates. Households would take preparedness actions based on their predictions of the event and resources on hand (Lindell & Perry, 2000). Hence, service expectations would influence a household's tolerance level for potential service disruptions.

Risk communication: Information promulgated by public officials regarding an extreme event largely shape public perception of and reaction to potential risks (Barnett & Breakwell, 2001; Fan et al., 2018). Communication between public agencies and the public affects societal expectations and people's perception of service disruptions (Parasuraman, Zeithaml, & Berry, 1985). The public can adapt to disturbing events if the information is well-communicated (Applied Technology Council 2016; Li et al., 2020). Reliable information about the threats, instruction on how to react in the hazard setting, and other forms of communication assist the community to better cope with the hazards and increase their zone of tolerance. For example, in the case of prolonged power outages, if the agencies inform the public early enough, households could take proper actions to reduce the adverse impacts.

Sociodemographic characteristics: Households' tolerance for service disruptions is also affected by social status (Baker, 2011; Dash & Gladwin, 2007; Stein, Buzcu-Guven, & Subramanian, 2014). In particular, vulnerable populations experience disparities in risks incurred due to disasters (Highfield, Peacock, & Zandt, 2014; Trump et al., 2017) as socially vulnerable groups are more likely to live in the neighborhoods prone to risks posed by the disasters, and they lack resources to prepare for and adapt to those risks (Applied Technology Council, 2016). The social vulnerability index (Flanagan et al., 2011) for disaster management organizes social vulnerability into four main categories: (1) socioeconomic status, (2) household composition/disability, (3) minority status, and (4) housing/transportation.

Among sociodemographic attributes, household income has a positive influence on hazard mitigation actions (Baker, 2011; Lindell & Perry, 2000; Russell et al., 1995) in preparation for upcoming disasters. Education and race are shown to relate to households' risk perception and preparedness actions (Lindell & Whitney, 2000; Muttarak & Pothisiri, 2012; Slovic, 1999). Racial minority groups are more vulnerable to natural hazards due to the language barrier, community isolation, income, and housing patterns (Fothergill, Maestas, & Darlington, 1999). Past studies also highlight the effects of the presence of elderly or young children on household risk perception and disaster preparedness (Baker, 2011; Barnett & Breakwell, 2001; Horney et al., 2007; Lindell & Whitney, 2000; Stein et al., 2014). The ownership of the residence, type of residence, and duration of residence have been shown to affect household's adjustments and adaptive actions (Baker, 2011; Horney et al., 2007; Lindell & Perry, 2000; Stein et al., 2014). Finally, the physical health of household members can affect their adequate service limit (i.e., households with a member having disability/mobility issue or chronic disease) (Van Willigen, Edwards, Edwards, & Hessee, 2002).

We devised the hypotheses (Table I) to empirically test the relationships among different components of the household service gap model. We identified a list of factors that affect a household's behaviors, actions, and responses during disasters from the literature. Then, by carefully examining the influencing factors, we selected the ones that could influence a household tolerance to service disruptions for further testing in the hypotheses. We conducted a survey of Harris County, Texas residents who experienced

Table I. Summary of the Hypotheses

No.	Hypotheses
H1	The higher the importance of service for satisfying needs, the smaller the zone of tolerance
H2	The greater the level of preparedness of a household, the greater the zone of tolerance
H3	Households having access to substitutes for service have a wider zone of tolerance
H4	Households having social capital have a greater zone of tolerance
H5	Households having prior experience with disasters have a greater zone of tolerance
H6	Households with expectations of more extensive service disruptions have a greater zone of tolerance
H7	Households which have access to more reliable information have a greater zone of tolerance
H8	Households from vulnerable subpopulations have a smaller zone of tolerance and hence experience higher hardship due to service disruptions
	(a) Households with lower income and education and minority ethnicity have a smaller zone of tolerance
	(b) Households with a member less than 10 years of age and/or more than 65 years of age have a smaller zone of tolerance
	(c) Households with a member having mobility/disability problem or chronic disease have a smaller zone of tolerance
	(d) Households who have lived in their residences for a longer time and homeowners of single-family houses have a greater zone of tolerance

Hurricane Harvey to test the framework in the context of power outages.

3. METHODOLOGY

Data were collected from the Harris County area in the aftermath of Hurricane Harvey, a Category 4 storm that made landfall in Texas on August 25, 2017. Harvey brought severe rainfall and mass flooding to the Gulf Coast. The proposed service gap model allows determination of the main factors behind risk disparity due to various infrastructure service disruptions. This study, in particular, concentrates on the electricity outages affecting Harris County residents during Hurricane Harvey. Power outages caused significant difficulty for the households during and in the aftermath of the storm. Approximately 336,000 Texas customers experienced power outages (CBS/AP 2017). Service disruptions and recovery times differed in length, and the impact varied among households. The focus of this study was on households who decide not to evacuate before the event. The responses indicating evacuation would not provide information regarding the disruptions in the services. During Hurricane Harvey, there was no mandatory evacuation in Harris County, and in fact, this made this study context a proper testbed for investigating the societal risks of such service disruptions for shelter-in-place households. A household survey was conducted in Harris County among those who experienced prolonged power outages during Hurricane Harvey. The empirical data from the survey was used to validate the proposed household service gap model and test the hypotheses. Fig. 3 shows the ZIP code map of areas affected by power outages during and after Hurricane Harvey. The sample included residences in ZIP codes which experienced both power outages and those that maintained full power to provide a basis for contrasting household responses and testing the hypotheses.

3.1. Survey Design and Instrument

A web-based survey was deployed through an online survey panel service in May 2018. An online survey panel service, Qualtrics, collected data from a sample population of the public (older than 18) in Harris County. The survey data were collected nine months after the event, which could cause recall bias; however, Hurricane Harvey was a catastrophic event, and people would still have a relatively clear memory about it. The subjects were recruited by Qualtrics from the different ZIP codes. Qualtrics is a private U.S. company with expertise in online data collection. Qualtrics data collection services are used by many academic institutions in the United States, and several studies reported results based on the data collected by Qualtrics. For this study, Qualtrics used a stratified sampling strategy from a census-representative panel to deploy the

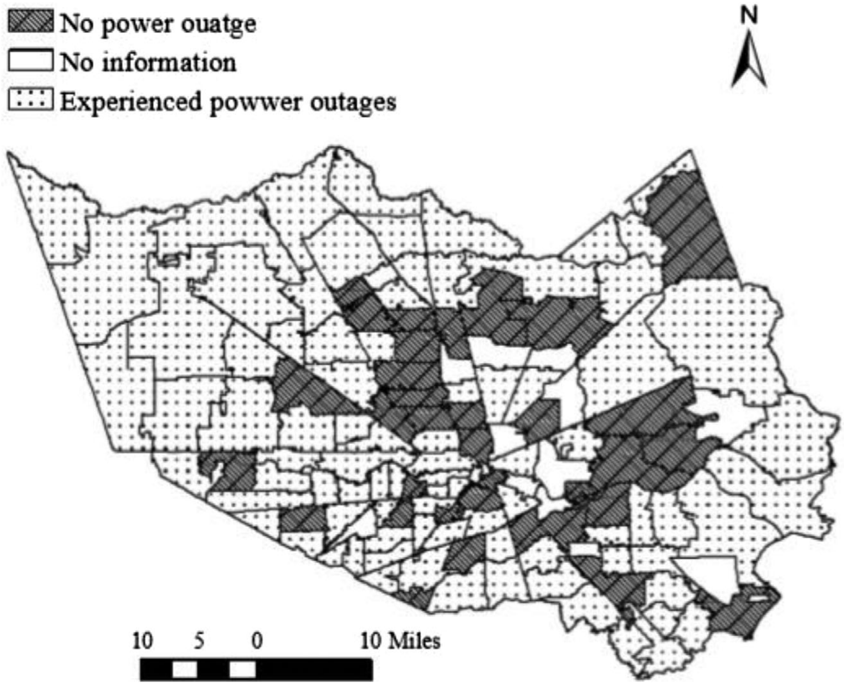

Fig 3. Power outages during the Hurricane Harvey.

surveys to subjects. An initial sample of 47 questionnaires was first distributed to check the quality of the questions, and a review of the results determined that the survey was ready for complete data collection. Finally, a sample of 715 responses was collected. The total sample includes distributed information from 126 ZIP codes out of all 145 standard ZIP codes of Harris County. Those with incomplete responses and those that had evacuated their households before Hurricane Harvey made landfall were eliminated from the analysis. After data filtering, 574 complete responses were utilized for the analysis.

3.2. Measures

The survey included questions related to the household zone of tolerance and experiences with Hurricane Harvey, service disruptions, as well as key demographic attributes. To measure their disruption level, respondents were asked to input the number of days they experienced power outage. The zone of tolerance of the respondents was then estimated by asking how many days they could tolerate power outages if a situation like Hurricane Harvey were to recur. To account for the buffer, respondents reflected on the number of days they have experienced electricity outages and reported the number of additional days they could tolerate power outages. Lastly, the self-reported hardship from the power outages was measured in a five-point Likert-scale ranging from Not at all (= 1) to A great deal (= 5). Table II summarizes how each influencing factor of tolerance zone was measured.

3.3. Analysis

Correlation analysis was used to test the hypotheses related to the influencing factors of the zone of tolerance (Table I). Correlation analysis examines if there is an association between the zone of tolerance and the influencing factors. However, this association is not linear and might be through the mediation of other variables due to the intercorrelation among the variables. Therefore, we implemented a Poisson regression model to account for the simultaneous effect of multiple factors on the zone of tolerance. Zone of tolerance was measured by the number of days that households could tolerate the service disruptions, and Poisson regression, which is a type of generalized linear models to deal with the count data was selected for modeling the data. Poisson distribution for the random component can take nonnegative values and is a right-skewed distribution (Agresti, 2007); therefore, this approach was an appropriate choice for modeling the zone of tolerance.

Table II. Measurement of the Influencing Factors of the Zone of Tolerance

Factor	Input
Household need for service	Not at all important (= 1) to important (= 5)
Level of preparedness	Not at all prepared (= 1) to over prepared (= 5)
Power-backup or substitute?	No (= 1) or yes (= 2)
Social capital	No (= 1) or yes (= 2)
Any relatives or close friends for assistance?	
Members of social groups in the community?	No (= 1) or yes (= 2)
Previous experience	No (= 1) or yes (= 2)
Experienced previous natural hazards?	
Access to reliable information	Never (= 1) to almost always (= 5)
Service expectation	Expected duration of service outages (Number of days)
Social demographic	Less than 2 years (= 1)
Age	2–10 years (= 2)
	11–17 years (= 3)
	18–64 (= 4)
	65 years or older (= 5).
Education	Less than high school (= 1),
	High school graduate or GED (= 2)
	Trade/technical/vocational training (= 3),
	Some college (= 4)
	Two–year degree (= 5)
	Four–year degree (= 6)
	Post-graduate level (= 7), and other (= 8)
Household income	Less than $25,000 (= 1),
	$25,000–$49,999 (= 2),
	$50,000–$74,999 (= 3),
	$75,000–$99,999 (= 4),
	$100,000–$124,999 (= 5),
	$125,000–$149,999 (= 6),
	or more than $150,000 (= 7)
Ethnic identity	White (= 0), minority (= 1)
Residence ownership	Nonowner (= 0)
	Owner (= 1)
Residence type	Multiple units/mobile home (= 1)
	Single-family home (= 2)
Chronic disease	No (= 1) or yes (= 2)
Difficulty in mobility	No (= 1) or yes (= 2)
Number of years living in Harris County?	Number of years

* The survey question asked the respondents about how many of the household members are in the specified age ranges and not the age of the responder.
** The survey question asked the respondents about the education level of the head of households.

4. RESULTS

The sociodemographic characteristics of the households in the survey data are displayed in Table III. Despite the low percentage of Hispanics due to the fact that the survey was conducted in English, the sample contains a sufficient diversity of the demographic information for the tests of the hypotheses. This study focused on investigating the association between the hypothesized variables. As a result, having a diverse population for studying the associative relationships in the model was more important than the exact representativeness of the study area sample (Lindell, 2008; Lindell & Hwang, 2008). Moreover, the large number of significant correlations among the variables (73 out of 171) in Table VI rejects the assumptions that the identified significant relationships are present because of the experimental-wise error. When using a $p \leq 0.05$ confidence level, one can expect approximately 9 (171×0.05) of correlations to become significant by chance. However, the number of significant correlations (73) is approximately eight times as many as what would

Table III. Sociodemographic and Characteristics of the Survey Respondents

Variables	Categories	Frequency	Percent (%)
Age	Less than two years	26	4.53
	2–10 years	76	13.24
	11–17 years	79	13.76
	18–64 years	423	73.69
	65 years or older	215	37.46
Education	Less than high school	10	1.74
	High school graduate or GED	62	10.80
	Trade/ technical/ vocational training	29	5.05
	Some college	92	16.03
	2-year degree	40	6.97
	4-year degree	199	34.67
	Post-graduate level	140	24.39
	Other	2	0.35
Household income	Less than $25,000	72	12.54
	$25,000–$49,999	115	20.03
	$50,000–$74,999	129	22.47
	$75,000–$99,999	76	13.24
	$100,000–$124,999	55	9.58
	$125,000–$149,999	44	7.67
	More than $150,000	83	14.46
Ethnic identity	White	394	68.64
	Hispanic or Latino	47	8.19
	Black or African American	87	15.16
	American Indian or Alaska Native	5	0.87
	Asian	24	4.18
	Native Hawaiian or Pacific Islander	1	0.17
	Other	16	2.79
Residence ownership	Owner	416	72.47
	Nonowner	158	27.53
Residence type	Single family home	431	75.09
	Multiple units/mobile home	143	24.92

Table IV. Summary Statistics of Hardship, Zone of Tolerance, Buffer, and Disruption

	Mean	Median	Standard Deviation
Self- reported hardship (Likert scale 1–5)	1.97	2.00	1.14
Zone of tolerance (days)	3.88	3.00	4.19
Disruption (days)	0.73	0	1.72
Buffer (days)	2.43	2.00	3.16

occur by chance. Thus, the empirical support in the model is not due to an experiment-wise error.

Table IV presents the summary of statistics for the hardship level, the zone of tolerance, buffer, and duration of service disruption that households experienced during Hurricane Harvey. Zone of tolerance, disruption, and buffer were measured in the number of days, and hardship level was determined by a Likert scale 1–5. Around 30% of the responders experienced power outages. The data from these households, along with those who did not experience the outages were used for testing the hypotheses related to the disproportionate risks and examining the determinants of the zone of tolerance. The zone of tolerance captures the capability of the households in tolerating the service outages and does not depend on the experiences of the individual households with the specific service disruption.

4.1. Zone of Tolerance as an Indicator of Household Susceptibility

The negative correlation between the hardship and the zone of tolerance in Table V shows that

Table V. Correlation among the Variables in Model 1 and Hardship

	Self- reported hardship	Zone of tolerance	Disruption
Self- reported hardship	–	–	–
Zone of tolerance	-0.23*	–	–
Disruption	0.50*	0.09	–
Buffer	-0.41*	0.89*	-0.15*

*significant at 1%.

households who had more tolerance to power outages expressed less hardship due to power outages. On the other hand, as the households experienced more days of power outage, they experienced more hardship, as shown by the positive correlation between the disruption and self-reported hardship in Table V. Finally, as the zone of tolerance increases and the service disruption decreases, the households will have more buffer and consequently lower level of hardship experienced by the households.

4.2. Disproportionate Risk Among Subpopulations

To test the hypotheses related to risk disparity due to service disruptions among vulnerable populations, we examined the self-reported hardship, level of service disruption, and the zone of tolerance of different subpopulations based on their income, race, education, and age.

4.2.1. Self-Reported Hardship

The hardship levels experienced due to the power outages are not equal across the subpopulations. Households with annual income less than \$50,000, households with a member less than 10 years of age, and households of racial minority reported experiencing a greater hardship than their compared subpopulations. Households with the highest education level less than a college degree and households with a member older than 65 years of age did not report a statistically significant greater hardship due to power outages.

4.2.2. Disrupted Service Level

The results related to comparing the duration of power losses experienced by different population subgroups did not show a significant difference. The nonsignificant *p*-values in the Mann–Whitney U test for all cases (all greater than 0.5) suggest that the extent of a power outage for various subgroups is not statistically different. Thus, the high level of hardship experienced by more vulnerable groups cannot be explained solely by the disruption exposure (duration).

4.2.3. Zone of Tolerance

Lower income households, racial minorities, and households with a member younger than 10 years of age were found to have a statistically smaller zone of tolerance in comparison with the other households among population subgroups. The zone of tolerance for the households with education less than a college degree and the households with a member older than 65 years of age was not statistically different from their comparison groups. Although these results are not statistically significant, in both cases, the groups with a smaller zone of tolerance reported experiencing a higher hardship from the power outages.

4.3. Factors Influencing the Zone of Tolerance

The hypotheses related to the factors influencing the zone of tolerance were tested. Table VI shows the correlation values between the influencing factors and the zone of tolerance, as well as correlations between different influencing factor pairs. The results of the Poisson regression model implemented to account for the simultaneous effect of the influencing factors are presented in Table VII. In the following paragraphs, the bivariate association of the zone of tolerance with the influencing factors and their association in the presence of other influencing factors are discussed.

4.3.1. Need

Testing hypothesis 1 showed a statistically significant correlation between a household's need for the service and the zone of tolerance. This finding suggested that households with a greater need for

Table VI. Intercorrelation Between the Influencing Factors of Zone of Tolerance

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Tolerance zone	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
2. Need	-0.13^{***}	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
3. Preparedness	0.11^{***}	0.01	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
4. Substitute	0.23^{***}	−0.03	0.12^{***}	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
5. Family & friends support	0.10^{**}	−0.03	0	0	–	–	–	–	–	–	–	–	–	–	–	–	–	–
6. Social groups	0.1	−0.02	0.08^{*}	0.1	0.12^{***}	–	–	–	–	–	–	–	–	–	–	–	–	–
7. Experience	0.14^{***}	−0.04	0.10^{**}	0.09^{**}	0.09^{**}	0.11^{**}	–	–	–	–	–	–	–	–	–	–	–	–
8. Residence type	0.13^{***}	−0.07*	0.09^{**}	0.11^{***}	−0	0.13^{**}	0.10^{**}	–	–	–	–	–	–	–	–	–	–	–
9. Service_exp	0.09^{**}	0.03	−0	0.09^{**}	0.08^{*}	−0	0.1	0	–	–	–	–	–	–	–	–	–	–
10. Information	0.12^{***}	0.08*	0.17^{***}	0	0	−0	0.1	0.1	−0	–	–	–	–	–	–	–	–	–
11. Household income	0.12^{***}	−0.01	0	0.13^{***}	0	0.16^{***}	0.10^{**}	0.28^{***}	0	0.1	–	–	–	–	–	–	–	–
12. Education	0	0	0.1	0	0	0.17^{***}	0.07^{*}	0.10^{**}	−0	0.1	0.44^{***}	–	–	–	–	–	–	–
13. Race minority	-0.12^{***}	0.13^{***}	−0	0	−0.1	-0.07^{*}	-0.18^{***}	-0.12^{***}	0	0	-0.21^{***}	-0.18^{***}	–	–	–	–	–	–
14. Age (10)	-0.07^{*}	0.06	−0.1	−0	0	−0	-0.15^{***}	0	0	−0	−0.1	-0.14^{***}	0.25^{***}	–	–	–	–	–
15. Age (65)	0.1	-0.09^{**}	0.09^{**}	−0	0.1	0.13^{***}	0.13^{***}	0.08^{*}	−0.1	0	0	0.08^{**}	-0.22^{***}	-0.25^{***}	–	–	–	–
16. Residence duration	0.10^{**}	−0.06	0.07^{*}	0.12^{***}	−0	0.10^{**}	0.18^{***}	0.24^{***}	0	0	−0	−0	−0	-0.21^{***}	0.29^{***}	–	–	–
17. Ownership	0.14^{***}	−0.05	0.1	0.17^{***}	0	0.17^{***}	0.17^{***}	0.48^{***}	0	−0	0.26^{***}	0.16^{***}	-0.20^{***}	-0.12^{***}	0.27^{***}	0.45^{***}	–	–
18. Mobility/disability	0	−0.07	0	0	−0	0	−0	0.07^{*}	-0.09^{**}	0	0.17^{***}	0.13^{***}	0	−0	-0.08^{*}	0	0.13^{***}	–
19. Chronic disease	0.10^{**}	0.05	−0.1	0	0.08^{**}	0.08^{*}	0.15^{***}	0	0.1	0	0	0.11^{***}	-0.23^{***}	-0.15^{***}	0.24^{***}	0	0.1	-0.30^{***}

*, **, *** Significant at 10%, 5%, and 1%, respectively.

Table VII. Poisson Regression Analysis Results

Influencing Factors	Estimate	Std. Error	Z-value	$\Pr(>\lvert z\rvert)$
(1) (Intercept)	−0.735	0.276	−2.667	0.007
(1) Need	−0.106	0.023	−4.57	0.000
(1) Preparedness	0.112	0.036	3.127	0.002
(1) Service substitutability	0.337	0.053	6.41	0.000
(1) Social capital	0.180	0.048	3.739	0.000
(1) Social groups	−0.018	0.049	−0.369	0.712
(1) Previous experience	0.285	0.085	3.37	0.001
(1) Service expectation	0.018	0.007	2.542	0.011
(1) Risk communication	0.117	0.025	4.586	0.000
(1) Household income	0.023	0.014	1.639	0.101
(1) Race minority	−0.155	0.058	−2.694	0.007
(1) Education	−0.024	0.015	−1.631	0.103
(1) Age +65	−0.017	0.052	−0.318	0.750
(1) Age −10	−0.045	0.074	−0.614	0.540
(1) Mobility/disability	−0.092	0.079	−1.169	0.242
(1) Residence duration	0.004	0.002	2.116	0.034

(*Continued*)

Table VII (Continued)

Influencing Factors	Estimate	Std. Error	Z-value	Pr($>|z|$)
(1) Ownership	0.021	0.076	0.277	0.782
(1) Residency type	0.171	0.074	2.304	0.021
(1) Chronic disease	0.154	0.051	3.041	0.002

a particular service had a smaller zone of tolerance for service disruptions. A household's level of need for electricity was significantly correlated with the racial ethnicity of households. Households representing racial minorities showed a higher need for electricity. However, the needs of the households remained significant when considering the effect of other variables in the model (Table VII).

4.3.2. *Preparedness*

Households' preparedness was positively correlated with the zone of tolerance. The more prepared households become for service disruptions, the greater their zone of tolerance. The small p-value for the preparedness level in the Poisson regression results suggested that the effect of preparedness is not mediated by other factors in the model.

4.3.3. *Service Substitutability*

Testing hypothesis 3 showed that households in possession of power back-up, usually a generator, had a significantly larger zone of tolerance for the power disruptions than those without power back-up. Having a substitute was a significant factor influencing the zone of tolerance for the power outages in the Poisson regression analysis.

4.3.4. *Social Capital*

Having social capital, such as friends and families to rely on during the disaster, was shown to be positively related to the zone of tolerance. In the case of participation in the social activities, the correlation, at a 95% significance level, was not significant. The regression analysis presented in Table VII also showed similar results and having a social capital influenced the zone of tolerance in the presence of other variables in the model.

4.3.5. *Previous Experience*

Having previous experience with natural hazards (hypothesis 5) had a significant positive effect on the zone of tolerance as reported in Table VI, and households with previous experience of natural hazards reported having a greater zone of tolerance. Although having previous experience had a positive relationship with the level of preparedness, substitutes, social capital, and sociodemographic characteristics, the results from the regression analysis showed that the simultaneous effect of these variables could not explain the influence of prior experience on the zone of tolerance.

4.3.6. *Service Expectation*

The analysis showed a significant positive correlation between the household's expectation of a power outage of extensive duration and the zone of tolerance (testing H6); Households who expected extensive power outage prior to Harvey's landfall indicated a greater zone of tolerance. The results from the Poisson regression also confirmed the significant association between the households' expectation of the power outages and their zone of tolerance for the service when controlling for the other variables in the model.

4.3.7. *Risk Communication*

Testing H7 showed having access to more reliable information had a positive relationship with the

Table VIII. Summary of Influencing Factors of the Zone of Tolerance

Influencing factors		Positive Impact	Negative Impact	Mediated by Other Factors
Need		–	√	–
Preparedness		√	–	–
Service substitutability		√	–	–
Social capital		√	–	–
Previous experience		√	–	–
Service expectation		√	–	–
Risk communication		√	–	–
	Household income	√	–	√
	Race minority	–	√	–
	Education	–	–	–
	Age +65	–	–	–
Sociodemographic characteristics	Age −10	–	√	√
	Mobility/disability	–	–	–
	Chronic disease	√	–	–
	Residence duration	√	–	–
	Ownership	√	–	√
	Residence type	√	–	–

zone of tolerance. Households with access to reliable information about power outages reported a larger zone of tolerance than those who did not. In addition, this variable seemed to influence the zone of tolerance when considering the effects of the other factors in the Poisson regression model.

4.3.8. *Sociodemographic Characteristics*

Supporting hypothesis 8a, higher-income and white households had a greater zone of tolerance; however, there was no significant association between education and zone of tolerance of the households. The Poisson regression analysis showed that while the effect of race was not mediated by other variables, the effect of household income on the zone of tolerance was no longer significant when controlling for other variables.

With regard to hypothesis 8b, households with a member less than 10 years of age were shown to have a smaller zone of tolerance in comparison with other households. However, the correlation for households with a member older than 65 years of age was not significant at a 95% confidence level. The small zone of tolerance of the households with a member less than 10 years of age was shown to be mediated by other factors when introducing the effect of the other variables in the model.

Rejecting hypothesis 8c, the results showed that having a member with the mobility/disability problem in the household did not have a significant association with the zone of tolerance to power outages. Households having a member with chronic illness reported having a larger zone tolerance (rejecting H8c). Moreover, the effect of this variable remained significant when considering the effect of other factors in the regression analysis.

Supporting hypothesis 8d, duration of living in residence, type of residence, and ownership status of the residence were positively related to the zone of tolerance. The effect of ownership was explained by other factors in the Poisson regression models, while the residence type and the duration of living in residence influenced the zone of tolerance. The summary of the results is presented in Table VIII.

5. DISCUSSION

The proposed framework of the service gap for assessing infrastructure services and how households would become affected by service disruptions was tested with the survey data. First, the positive correlation of disruption level and hardship shows that generally the greater the level of disruption of services, the more strongly the households will experience difficulty. Second, the negative correlation of the zones of tolerance with hardship suggests the presence of the tolerance zone for services, which makes clear why some households will be more affected by service outages and require more attention during disasters. Third, the significant negative correlation of hardship level and buffer, which captures the effect of both the disruptions and the zone of tolerance, shows the importance of considering integrated physical and social features of risks.

The highly reported hardship of low-income households, households with members less than 10 years of age, and racial minorities show that the realized impacts are not experienced the same way by all subgroups. One may assume that the reason why more vulnerable subgroups have experienced more hardship is that the exposure of these groups to the service disruptions was higher, and the high level of disruption could be the main reason for this difference. For example, it might be the case that the low-income group lives in areas prone to electricity disruption. It was, however, that the degree of service disruption experienced by this subgroup did not differ from one another; and their varying zone of tolerance to withstand that impact was the main reason for the existence of the disproportionate risk within the community.

The factors that might affect the adequate service level and the zone of tolerance of the households in Fig. 2 were tested. First, the household's need for service was strongly correlated with the zone of tolerance, and households with higher need for power expressed less tolerance for disruption. These households may have an urgent need to access the service; for instance, some responders in the survey stated that they need power for the use of medical devices or refrigerated storage of the medication. Therefore, these urgent needs make the households more susceptible to service disruptions.

As supported by the results, a household's overall preparedness and availability of a substitute showed a positive correlation with the zone of tolerance. The results also suggest that having a substitute and the level of preparedness are strongly correlated, but the effect of preparedness could not be explained by the substitutes available to the households. The preparedness level of households is affected by the previous experience of the households, the reliability of the information that they receive, residence type, and the residence duration, all of which are supported by the previous literature (Baker, 2011; Horney et al. 2007). Moreover, having a substitute for the power disruptions is related to income, home ownership, and residence type. As proposed by Lindell and Hwang (2008), hazard mitigation actions that affect the household's adjustment, such as buying a generator, require the large capital expense and will not be adapted when the occupant moves. Thus, owning a generator is affected by the residence type, home ownership, and household income.

Having social capital, such as family and friends, was significantly related to the zone of tolerance. Households with a larger base of social capital could rely on their social networks in terms of meeting their basic service needs or providing accommodation if they decide to evacuate because of service losses.

A household's previous experience with natural hazards has been shown to be a significant influencer of the zone of tolerance. Past experience and having a power back up have a strong correlation with each other. These results are supported by other studies about the relationship between past experience and hazard adjustments (Lindell & Hwang, 2008; Lindell & Prater, 2000). The high correlation between previous disaster experience and the zone of tolerance, however, could not be explained by the existence of a substitute or level of preparedness of the household, and it was found that the previous experience affects the zone of tolerance directly.

Households with a higher expectation of service disruptions have a larger zone of tolerance. The effect of the expectation from the service could not be explained by the other variables. Households with higher expectations of disruptions perceive the potential risks and are more likely to take protective actions to deal with the expected disruptions (Lindell & Hwang, 2008). The protective actions result in a greater zone of tolerance.

Accessibility to reliable information of power loss status had a positive impact on the zone of tolerance. The more reliable and timely information households receive regarding service disruption, the better decisions members can make for coping with potential risks. The significant relation of information reliability and preparation level shows that reliable information can assist the households to better prepare for the upcoming hazards and to make wise decisions. Risk communication influences the zone of tolerance both directly and through the preparedness level, underscoring the importance of providing the proper information for residents of affected areas.

Sociodemographic characteristics, such as income, home ownership, duration of residency, and the type of residents, were significantly related to the zone of tolerance. The effect of income and ownership status on the zone of tolerance is explained by other variables. Households with high income and homeowners are more likely to live in single-unit housing and adopt the proper adjustments, such as buying a generator to cope with the potential threat of service losses. The longer the period of residency, the more likely residents had previous experience with natural hazards, explaining why the duration of the residency affects the zone of tolerance.

Education did not appear to be a significant factor influencing the households' tolerance of service disruptions. Racial minorities were observed to have a low tolerance zone for the power outages. This finding is aligned with existing literature on the differing capabilities of the racial minorities in a disaster setting (Fothergill et al., 1999; Lindell & Hwang, 2008). Racial minorities were observed to have less experience in disasters, lower income, and a lower percentage of home ownership. These factors could be the reasons why these groups are more vulnerable to service disruptions. Households with a member less than 10 years of age reported having a lower tolerance to disruptions. The effect of age, however, is explained by other variables.

There are some limitations in the proposed framework that could be addressed in future studies. The influencing factors affecting the zone of tolerance were identified based on the review of literature related to people's behaviors and responses during disasters. However, other relevant factors, such as the political economy or situational factors, might also affect a household's tolerance level to service disruptions. Therefore, future studies could investigate the significance of other variables that may influence households' tolerance to service disruptions.

6. CONCLUSION

Service disruptions in disasters are experienced differently by subgroups within the community, and the vulnerable population tends to suffer more from such losses. Low-income households, racial minorities, and households with young children have reported experiencing more hardship from the service disruptions than others. This article investigated the reason for this societal risk disparity by asking: "What are the determinants of societal risk disparity due to infrastructure service disruptions?" To answer this question, first, the exposure of the households to the service disruptions was investigated to evaluate whether the vulnerable populations live in areas with higher duration of service disruptions. The results did not show a significant difference in the threat exposure (i.e., duration of the service outages) among vulnerable populations and others. The results suggested that the variation in societal risks of service disruptions was due to differences in the household-level susceptibility characterized by the tolerance zone. The tolerance zone captures a household susceptibility to service disruption impacts based on households' needs for services and capabilities to withstand the risks posed by the service disruptions. The survey analysis results confirmed that the zone of tolerance is associated with the hardship endured by households.

The second question guiding the study was about "What significant factors affect the tolerance of households from different subpopulations to potential service disruptions?" The study identified the influencing factors and tested their significance through the use of empirical data from Harris County in the aftermath of Harvey. Sociodemographic characteristics of households, such as income, age, race, homeownership, and the type of residence, all directly or indirectly influence the zone of tolerance. This finding explains the underlying mechanisms that influence the societal risks of households to infrastructure service disruptions (power outage in the case of this study) and the presence of disparities in household-level risks. For example, lower-income households were found to have a lower tolerance to power outages. The lower tolerance of these households could be due to the lower resources these households have to withstand the service outages. The zone of tolerance is a function of a household needs, as well as their capabilities. For example, households that have members who are dependent on powered medical devices have a much lower tolerance for power outages. The existence of and access to service substitutes, such as generators, affect a household capability and thus influence the zone of tolerance. Informing households about protective actions (such as preparedness, adjustments, and information seeking) could improve their capability, and subsequently, their zone of tolerance to service disruptions. For example, providing timely and reliable information regarding expected service outages and instructions regarding dealing with service losses can improve households' preparation actions and their zone of tolerance. Finally, the effect of social capital on the zone of tolerance highlights the importance of social ties and support for coping with the impacts of prolonged service outages.

This study proposed a framework for examining the societal risks of infrastructure service disruptions by considering variations in the households' level of tolerance to service disruptions. The study emphasizes the significance of incorporating social considerations in infrastructure resilience assessments. The proposed service gap model characterizes the underlying mechanisms affecting households' susceptibility when facing prolonged infrastructure service disruptions. Households from various subpopulations have different levels of tolerance (susceptibility), and hence investigating inequalities in household-level susceptibility and risk enables better prioritization of resources to reduce the risk disparities for the vulnerable population.

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