ADDRESSING INEQUITIES IN SERVICE DISRUPTIONS WITH HUMAN-CENTRIC INFRASTRUCTURE RESILIENCE: AN EMPIRICAL ASSESSMENT OF HOUSEHOLD-INFRASTRUCTURE INTERACTIONS DURING DISASTERS

A Dissertation

by

JENNIFER SARA DARGIN

Submitted to the Graduate and Professional School of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Chair of Committee,	Ali Mostafavi
Committee Members,	Maria Kouliou
	Michelle Meyer
	David Ford
	Rabi H. Mohtar
Head of Department,	Zachary Grasley

May 2022

Major Subject: Civil Engineering

ABSTRACT

Natural disasters place tremendous stress on critical infrastructure systems by testing their service reliability under extreme condition. Prolonged service disruptions can pose serious threats to the physical, emotional, and well-being of residents in a community. In fact, critical infrastructure such as transportation, power, water, and communication systems are vital to maintaining the structure of a community. In the standard infrastructure resilience model (Fig.1), the goal is to eliminate the loss of service functions and improve the rapidity of function restoration in systems. However, this model fails to consider the variation in the sociodemographic characteristics of subpopulations and the extent to which vulnerable populations (e.g., low-income families and racial minorities) are disproportionately exposed to risks due to service disruptions. As a result, there is a lack of fundamental information about household interactions with infrastructure services in disasters, and more specifically, how these interactions differ with respect to different subpopulation groups. Understanding the disparities in infrastructure disruption impact is essential to integrating the needs of diverse populations into planning and prioritization of resilient infrastructure while mitigating impacts to the most vulnerable members of society when infrastructure services are disrupted. Therefore, our research study holistically views the disaster impact on individual households through four dimensions: the experienced hardship, the extent of exposure, the zone of tolerance, and well-being impact.

To address these shortcomings, a new framework for a human-centric infrastructure service model that conceptualizes the association between humans (in terms of well-being and hardship) and infrastructure (in terms of service provisions) is developed and demonstrated using empirical data collected from a household survey and analyzed using correlation analysis. In the first study, correlation analysis is used to confirm an empirical relationship between well-being in households

and infrastructure service disruption. It further establishes the existence of inequitable impacts in service disruptions on vulnerable population groups. A second study seeks to understand how social media is used for information communication behaviors surrounding different infrastructure service disruptions using logistic regression models. Existing disparities among vulnerable groups can be exacerbated by differences in social media access and use as tools for disaster and service disruption communications. The third study employs Structural Equation Models (SEM) to develop a systems-level understanding of household-level processes related to demand and access to FEW services during disasters with respect to differential household experiences. The final study of the dissertation uses Classification and Regression Trees (CART) to analyze underlying pathways of well-being impact disparities in vulnerable groups and different infrastructure services. Collectively, the studies of this dissertation advance the understanding of social inequalities in exposure and hardship experienced due to infrastructure service disruptions in disasters. In particular, the findings provide the much-needed empirical information necessary to uncover the extent to which subpopulations in a community experience varying levels of the disaster impact due to infrastructure system disruptions. Hence, the study contributes to establishing the fundamental knowledge needed for a paradigm shift towards a more equitable resilience approach in infrastructure systems.

DEDICATION

This work is dedicated to Asad, my dear husband, who has been my greatest source of support and motivation throughout my PhD journey, and our first son, Ali Faizan, who joined us along the way.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supervised by a dissertation committee consisting of Professors Ali Mostafavi, Maria Kouliou and David Ford of the Department of Civil and Environmental Engineering, Professor Rabi H. Mohtar of the Department of Biological and Agricultural Engineering at Texas A&M University, and Professor Michelle Meyer of the Department of Landscape Architecture and Urban Planning at Texas A&M University.

Funding Sources

Graduate study was supported by a graduate research assistantship from Texas A&M University and research funds from National Science Foundation (NSF). This work was also made possible in part by National Science Foundation under Grant Number Learning Award. Its contents are solely the responsibility of the authors and do not necessarily represent the official views of the National Science Foundation.

TABLE OF CONTENTS

Page

ABSTRACT……………………………………………………………………………………ii

DEDICATION………………………………………………………………………………iv

CONTRIBUTORS AND FUNDING SOURCES………………………………………v

LIST OF FIGURES…………………………………………………………………….....ix

LIST OF TABLES………………………………………………………………………. xi

CHAPTER 1: INTRODUCTION 1

Problem Statement 1
Study Significance...3
Literature Review 4
Knowledge Gaps... 8
Research Objectives...13
Research Questions 14
Theoretical Framework... 14
Data...15
Research Approach...17

CHAPTER II: STUDY 1 - HUMAN-CENTRIC INFRASTRUCTURE RESILIENCE: UNCOVERING WELL-BEING RISK DISPARITY DUE TO INFRASTRUCTURE DISRUPTIONS IN DISASTERS 22

Research Scope... 26

Conceptual Framework 31
Materials And Methods 37
Statistical Approach 43
Results 46
Discussion 56
Future Work 62
Concluding Remarks 64

CHAPTER III: STUDY 2 - VULNERABLE POPULATIONS AND SOCIAL MEDIA USE IN DISASTERS: UNCOVERING THE DIGITAL DIVIDE IN THREE MAJOR U.S. HURRICANES 66

Introduction 67
Research Scope 70
Background 71
Methodology 80
Results And Discussion 88
Conclusion 106

CHAPTER IV: STUDY 3 - ASSESSMENT OF HOUSEHOLD-LEVEL FOOD-ENERGY-WATER NEXUS VULNERABILITY DURING DISASTERS 109

Introduction 110
Conceptual Framework 116

Methodology 125
Results 130
Discussion 141
Concluding Remarks 148

CHAPTER V: STUDY 4 - DISSECTING HETEROGENEOUS PATHWAYS TO DISPARATE HOUSEHOLD-LEVEL IMPACTS DUE TO INFRASTRUCTURE SERVICE DISRUPTIONS 151

Introduction 152
Methodology 154
Study Context 159
Statistical Analysis 166
Results 168
Discussion 186
Concluding Remarks 198
Acknowledgments 200

CHAPTER VI: CONCLUSION 201

Key Findings 202
Theoretical And Practical Contributions 204
Recommendations For Future Work 207

REFERENCES 209

APPENDIX A 232

APPENDIX B 238

APPENDIX C 254

LIST OF FIGURES

Page

Figure 1: Equitable infrastructure resilience: integrating societal dimensions into standard infrastructure resilience framework (adapted from Esmalian, Dong, Coleman, and Mostafavi (2019) 2

Figure 2: Theoretical Framework 15

Figure 3: Survey Response distribution over study areas: Harris County (a), North Carolina (b), Georgia, Florida, Alabama (c). 16

Figure 4: Dissertation Structure 21

Figure 5: Infrastructure resilience and well-being framework 32

Figure 6: Distribution of households in the study area, Harris County, Texas 40

Figure 7: An analytical approach for measuring subgroup well-being disparity 44

Figure 8: Well-being and transportation disruption experience correlation matrix for Asian Households (Left), Black and African American households (Right) 54

Figure 9: Service disruption characterization. 59

Figure 10: Infrastructure types checked on social media during storms (%) 97

Figure 11: FEW nexus-Disaster Framework. 119

Figure 12: Model 1 pathway diagram 136

Figure 13: Conceptual framework, Study 4 156

Figure 14: Visual representation of the data sample stratification process.. 162

Figure 15: Variable importance in the CART model for all population groups (combined dataset).. 172

Figure 16: CART decision tree for low-income households experiencing water disruptions 177

Figure 17: CART decision tree for low-income households experiencing food infrastructure disruptions. 179

Figure 18: CART decision tree for white households experiencing water disruptions 183

Figure 19: CART decision tree for minority households experiencing water disruptions. 184

LIST OF TABLES

Page

Table 1: Adapted measures for well-being impact assessment 35

Table 2: Measurement of the influencing sociodemographic factors of household well-being disparities. 42

Table 3: Sociodemographic characteristics of households in the survey 46

Table 4: Subgroup populations experiencing disparity by well-being dimension and infrastructure service 47

Table 5: Characterization of racial and ethnic groups by the strongest associated well-being and infrastructure disruption 49

Table 6: Characterization of Income groups by the strongest associated well-being and infrastructure service 50

Table 7: Characterization of Age groups by the strongest associated well-being and infrastructure service 51

Table 8: Characterization of Health groups by the strongest associated well-being and infrastructure service 52

Table 9: Household Survey Data Variables 85

Table 10: Reported Disparities among population groups according to ANOVA 1-way tests 89

Table 11: Information checked during storms 98

Table 12: Social media platform and information seeking activity 100

Table 13: Survey Measures, Study 3 123

Table 14: Household Nexus Relationships Based on Household Survey Responses 131

Table 15: Bivariate analysis - Underlying Characteristics of FEW Vulnerable Households 134

Table 16: Summary of Model Performance Indices 137

Table 17: Total, direct, and indirect standardized effects of urban attributes, preparation behaviors, infrastructure disruptions, and social factors on FEW Vulnerability 141

Table 18: Independent variables of household-infrastructure resilience used in CART models 163

Table 19: Dependent variables used in CART models 163

Table 20: CART tree overview of decision node classification by hardship level and vulnerability type. 170

Table 21: Model performance statistics: accuracy, specificity, sensitivity based on high hardship class. 171

CHAPTER 1: INTRODUCTION

PROBLEM STATEMENT

Among other challenges that burden the infrastructure systems in the United States including budgeting and funding, climate change, inflexibility, and maturation, Chester et al (2019) recognize the critical challenge of designing infrastructure systems that foster social and environmental well-being. There has been more recognition over the years from stakeholders in engineering and construction disciplines that infrastructure systems need to be 'people focused'(Jennifer, Mark, & Gurdur, 2020), and outcomes and goals of infrastructure need to be driven by the needs of communities they serve (Bartos et al., 2016; Jennifer et al., 2020; Kane & Vajjhala, 2020). This translates to "measuring, and addressing our infrastructure challenges based on the needs of users of future and existing systems" in real-world applications (Kane & Vajjhala, 2020). National research institutions based in the US (NRC, NIST, NIAC) have further highlighted the inadequacy in the fundamental information available about household interactions with infrastructure services in disasters. Integrating the needs of diverse populations into planning and prioritization of resilient infrastructure will effectively lead to more resilient households and communities (NRC State of Resilience Report). Therefore, human-centric approaches to infrastructure resilience research are needed to advance our fundamental understanding of household-level service disruption. This understanding will ultimately reduce the risk disparity of vulnerable populations to service disruptions and integrate social equity into prioritization and planning of infrastructure.

The extent to which infrastructure service disruptions create disproportionate risks and experiences for different sub-populations of a community during disasters and the underlying factors of impact disparity remains understudied and challenging to quantify. As a result, these factors, while needed for minimizing inequities in service quality and disruption impacts, are left out from general disaster and infrastructure resilience planning and decision-making efforts**.** Systems need to be designed to withstand both hazard conditions (Godschalk, 2011) and provide equitable service to the communities they serve (Batouli & Mostafavi, 2018; Davis, 2007; Mostafavi, 2018). Neglecting people who rely on certain infrastructure services to support or sustain life and well-being disproportionately exposes segments of the population to more significant risks and the likelihood of requiring emergency assistance during disasters (FEMA - U.S. Department of Homeland Security, 2017). Resilience planning and emergency management stakeholders are therefore left with a complex task of determining which at-risk populations should be given priority in the allocation of limited resources (Kontokosta & Malik, 2018).

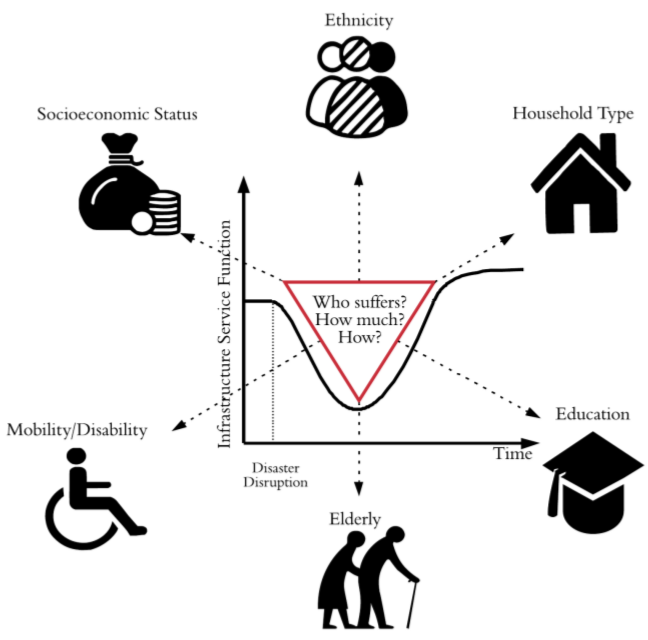


Figure 1: **Equitable infrastructure resilience: integrating societal dimensions into standard infrastructure resilience framework (Reprinted from Esmalian, Dong, Coleman, and Mostafavi (2019).**

STUDY SIGNIFICANCE

The purpose of this study is to first develop a human-centric approach for understanding household-infrastructure systems during disasters. The approach will be used to advance our understanding of human-centric household factors that influence hardship outcomes due to service disruptions during disasters by: (1) Identifying the points of intervention to mitigate well-being impacts in households due to service disruptions in water, energy, food, road transportation, communications, and solid waste services., and (2) Identifying the different pathways leading to well-being impact(s) due to different service disruptions and explore the differences in pathways across vulnerable population groups associated with income and ethnicity.

The findings of this study will identify not only the extent to which infrastructure service disruptions create disproportionate risks for different sub-population groups but offer explanations of hardship disparities and insights for intervention strategies that can improve household-infrastructure system resilience. The following section provides an overview of key background information on standard and human-centric reliance and the disparate impacts of infrastructure service disruptions during disasters to support the importance of this study. This chapter introduces the existing challenges and knowledge surrounding the household-level experience with infrastructure disruptions during disasters, outlines the guiding research objectives and research questions and provides an introduction of the theoretical framework and methodological approaches taken to address the research questions.

LITERATURE REVIEW

Inherent Susceptibility to Disasters and Service Disruptions

Households have different capabilities for tolerating service disruptions (Esmalian et al., 2019). Knowing which human capabilities are most valued is important for identifying which infrastructure services support those capabilities. (Clark, Seager, & Chester, 2018). The capability approach (Lindell, Prater, Perry, & Nicholson, 2006) emphasizes that people have different abilities to withstand disruptions as a result of different abilities to use resources available (Clark et al., 2018). the most critical infrastructures should be understood as those that are vital for protecting or providing essential human capabilities.

Social vulnerability in disaster management emerged from the realization that socioeconomic factors affect community resilience (Juntunen, 2005; Dargin & Mostafavi, 2020). During disasters, infrastructure disruptions exacerbate many socioeconomic impacts, including health, social, economic, and environmental consequences (Cheng, 2016). Vulnerable populations referred to in this framework have been derived from the Social Vulnerability Index (SVI) (Flanigan et al., 2011) and include racial or ethnic minorities, children, elderly, socioeconomically disadvantaged, and those with certain medical conditions.

The disparities in the societal impacts of infrastructure disruptions are due not solely to the higher exposure of certain households (Esmalian, Dong, & Mostafavi, 2021). Households intrinsically have different levels of tolerance to cope with disruptions (Esmalian et al., 2019; Esmalian et al., 2021). An important step to advance the theory of or framework for human centric infrastructure is to identify these pathways and identify which pathways are mainly influenced by which kind of factors that could be improved through infrastructure, vulnerability reduction or infrastructure improvements, and what pathways are more governed by factors that could be kind of disrupted or intervened by household level interventions such as risk communication or better awareness. The determinants of the disparities in the susceptibility to the service disruptions have been attributed to inherent factors of households including the sociodemographic characteristics of the households, their capabilities, expectations and needs, protective actions, and risks perceptions (Chakalian et al. 2019; Coleman et al. 2019, 2020; Dargin et al. 2020; Esmalian et al. 2019a; Mitsova et al. 2018). While these studies have improved the understanding of the factors influencing the susceptibility of households, they do not demonstrate how the unique pathway to well-being impacts due to service disruptions are different.

Standard Infrastructure Resilience Approaches

The NIPP and other prominent policy documents (DHS 2009, 2013; The White House 2011, 2013) do not give necessary attention to how human resilience may contribute to or detract from infrastructure resilience nor guidelines for addressing the interdependence of human behavior and infrastructure resilience (Thomas, Eisenberg, Seager, & Fisher, 2019). In response, the theory and discussion of *human centric infrastructure* is growing rapidly and there is growing interest in understanding human-infrastructure interactions during disasters and the variations for different populations.

I*nfrastructure resilience* is a system's ability to withstand, respond to, and recover from disruptions (Poulin & Kane, 2021). Standard practices of infrastructure planning and management design are based on two primary assumptions. First, infrastructure systems based on histories of extreme events (Bocchini, Frangopol, Ummenhofer, & Zinke, 2014). Water pump systems, for example, are retrofitted based on historical precipitation events (Rosenzweig et al., 2007). Electricity transmission lines are designed within limits of how much power they can move while maintaining safe operating conditions relative to air temperatures (Bartos et al., 2016). Bridges are designed to be able to withstand certain flow rates in the rivers they cross (Chester et al., 2020). However, in the United States and countries throughout the world, these historical thresholds are being exceeded more frequently as more intense weather events occur (Cheng & AghaKouchak, 2014). Secondly, the conventional engineering-based infrastructure resilience models assume the robustness of systems and structures to be linear or homogenous for all service populations. As a result, such models do are unable to fully consider the different subpopulations of a community use, access, and rely on the infrastructure and respond to service disruptions in different ways.

In standard practices, resilience curves are used to communicate quantitative and qualitative aspects of system behavior and resilience to stakeholders of critical infrastructure (Poulin & Kane, 2021). Resilience is multidimensional, and this multidimensionality needs to be reflected in current and future infrastructure resilience models to determine not only who is at greatest risk, but why and what factors place them in this threshold. An infrastructure resilience approach must consider multiple interpretations and perspectives of resilience to account for people as dynamic components of socio-technical systems ((Thomas et al., 2019). Thomas et al. (2019) posit that the National Academy of Science (NAS) has put forth the most comprehensive definition of resilience that brings together the resilience of socio-technical systems in one. The National Academy of Sciences (NAS) describes resilience as the ability to plan for, absorb, recover from, and adapt to actual and possible disruptive events (Cutter et al. 2012). Moreover, an important factor in this definition is the ability to anticipate and prepare for unknown disruptions (Hollnagel and Fujita 2013) creating the presumption that humans are involved. The capacity to plan and pre- pare for possible threats and mitigate potential risks also engages learning from prior experiences to develop strategies for resilient pathways. The NAS definition of resilience integrates the various resilience concepts shared among different perspectives and applications including psychology and engineering (Connelly et al. 2017; Wood et al. 2018). The NAS definition is therefore both broad for socio-technical context and practical for infrastructure design, operation, and management (Thomas et al., 2019).

Human-centric Infrastructure Resilience

The concept of human-centric infrastructure planning and management is becoming recognized as a pivotal component of transforming existing infrastructure systems and building new ones (Kane & Vajjhala, 2020). The United Nations Development Program (UNDP) recognizes the important role that infrastructure systems have in facilitating well-being in people and the society and the criticality of including well-being in the discussion of resilience (UNDP 2014; (Clark et al., 2018). The role of people's capabilities, or available choices, is a critical component in minimizing the adverse impacts of disruptive events (Clark et al., 2018). It is argued that increasing the capabilities of people is correlated with increased capacity to respond to and recover from adverse events such as natural disasters and service outages (UNDP 2014; (Clark et al., 2018). Applying human-centric resilience into practice is therefore an essential component of infrastructure resilience that cannot be ignored from decision-making processes surrounding infrastructure planning, prioritization, and management.

The study of 'human-centric' infrastructure system resilience at the household level, however, is still in its nascency and the role of infrastructure system resilience at the household level has only recently begun to be investigated (Esmalian, Coleman, Mostafavi, Dargin). Little existing work explicitly or systematically considers needs, expectations, and adjustments that influence the network dynamics of household service disruptions in disasters (Mostafavi and Ganapati 2019) and why certain households are more resilient in face of disruptions. The inadequate empirical information about the underlying mechanisms and extent of households' susceptibility to infrastructure service disruption has led to the weak consideration of the human-centric aspect in assessing the societal risks of such hazards (Mostafavi and Ganapati 2019).

Conventional engineering-based approaches to infrastructure retrofitting and repair emphasize fail-proofing systems that withstand risks of a specified measure. For example, storm-water infrastructure can be designed to withstand certain levels of sea level rise or retrofitted to withstand a 1,000-year event as opposed to a conventional 100-year event (Miller and Chester, 2017). A resilient approach to infrastructure development and management is one that emphasizes the capacity for flexibility, agility, and adaptability (Chester, 2019), and when systems do fail, the consequences to human life and the economy are minimized (Chester et al., 2018). Examples of resilient infrastructure services include deploying power microgrids ahead of hurricanes (Brodie, 2017), using crowd-sourced data for real-time flooding updates where conventional remote monitoring sensors are unavailable to communicate accurate road hazards and inform safe and temporary driving routes.

KNOWLEDGE GAPS

The goal of human-centered approaches to infrastructure resilience is to improve social equity in communities. Measures of societal progress thus need to be able to understand the diverse experiences. The integration of human-centric measures into existing infrastructure resilience models has previously been limited by then absence in sufficient empirical knowledge regarding the household-level interactions with infrastructure services during disasters. Specifically, there have been limited studies that empirically evaluate the extent to which disruptions in infrastructure system services impact subpopulation groups differently and how these impacts relate to the wellbeing of households.

Gap 1: Infrastructure System Risks & Vulnerability

Existing literature surrounding infrastructure resilience focuses on physical systems' performance, and the human-centric aspects of infrastructure resilience remain significant under-studied. There are limited studies to empirically evaluate how disruptions in infrastructure influence different aspects of well-being for different sub-populations and systematically capture the differential experiences that different vulnerable sub-populations have due to infrastructure disruptions. Disruptions of infrastructure services impose different levels of risk to residents' well-being, and the service disruptions will not be experienced the same way by different population sub-groups in the community. Pre-existing household characteristics such as age, income, and minority status, may magnify the impact of a natural disaster (Rufat et al. 2015), and leave them disproportionately affected by disasters and have shown to suffer more from the impacts of the infrastructure services interruptions ((Buckle et al. 2000; Gamble et al. 2013; Marsh et al. 2010; Peacock et al. 2014). Current infrastructure resilience models are unable to measure disparate service disruption impacts. As infrastructure systems become "smarter," resilience plans are at risk of becoming less in touch with the households for whom they serve (Falco, 2015). As a result, lifeline systems assume that all community members hold equal expectations and needs from infrastructural services and are impacted equally by service disruptions.

Gap 2: Well-being Disparities

Very few, if any, infrastructure resilience or disaster recovery models exist that represent variables of community well-being or public health (Mostafavi & Ganapati). This limitation is mainly due to the lack of empirical information that specifies the relationship between infrastructure disruptions and various elements of human well-being for different sub-populations. The construct of well-being has been recognized as a central factor in resilience to disaster impacts (Brown et al. 2011; Baggio et al. 2007; Kellezi et al. 2008; Kirmayer et al. 2009; Nyamwanza et al. 2012; Uchida et al. 2014; Capic et al. 2016; Badland et al. 2014), wherein disruptions to critical services have consequently impacted the well-being of households, individuals, and communities affected (Norris et al. 2002; Ursano et al. 2007; Shear et al. 2011). Conversely, well-being was associated with greater resilience to disaster impacts and the ability for communities to recover (Institute of Medicine, 2015). The impact of natural disasters has historically been quantified by physical measures, such as the number of damaged buildings, the cost of community rehabilitation, and total fatality or injury rate. While these measures might indicate the well-being state of affected households, there are a couple of issues with their use as social impact indicators. First, no current study has been carried out to empirically assess the relationship between well-being and the physical destructions of natural hazards. Second, these technical measures fail to capture the differential pathways and mechanisms through which households experience disruption impacts. Including measures of well-being defined as a person's cognitive and affective evaluations of his or her life" (Diener & Diener, 2002), can help identify how infrastructure systems integrate with household systems at a 'human' level to ensure the equitable provision of infrastructure services to the community.

Gap 3: Cross-Disciplinary Knowledge

Infrastructure resilience and disaster resilience are inextricably linked. The 2008 Wenchuan Earthquake demonstrated that enormous losses were largely attributed to failures of built environment, which consequently affected local emergency response and external aid (Wang et al., 2017). Moreover, the discussion of resilience is incomplete without addressing the flaws in current approaches that lead to disparate well-being outcomes in civilians during disruptive events. Disaster science and social science research have extensively established that vulnerable population groups are predisposed to higher risks during disasters (Buckle, Mars, and Smale, 2000; Gamble et al., 2013; Marsh, Parnell, and Joyner, 2010; Peacock et al., 2014). Initial assessments of the 2021 Texas Winter Storm have uncovered the inequitable impacts that critical infrastructure systems disruptions, namely power and water, have on communities, where low socioeconomic households experienced outages “first and for the longest” (Bullard, 2021). “Exclusionary zoning,” imbedded in land use and transportation policies since the 20th century, has caused policy makers and leaders to overlook or intentionally leave out the needs of lower-income households and minority communities when building and maintaining our infrastructure (Chester, 2016).

The synergies between social vulnerabilities, disaster resilience, and infrastructure resilience have only recently begun to be investigated with empirical research. Unsurprisingly, existing research has found that the impacts of infrastructure system failures during disasters are not equal in communities, and socially vulnerable populations are disproportionately affected by such service disruptions (Coleman et al. 2019; Dargin, J., Mostafavi 2020; Esmalian 2019) and cause varying levels of risks to the well-being of affected communities and how households are impacted (Dargin et al., 2020). Infrastructure service outages not only impose different levels of risk to the well-being, but the mechanisms through well-being impact is experienced is also different (Dargin & Mostafavi, 2020). Kontokosta and Malik (2018) found that resilient neighborhoods were shown to better withstand disruptions and return to normal activity patterns more quickly recover to pre-event functional capacity. The household well-being disparity model constructed by Dargin et al. (2020) shows that physical, urban, sociodemographic, and behavioral attributes are integrated and collectively affect the vulnerability of households to critical service disruptions. Given that ecological, technological, and human systems interact in increasingly uncertain and complex ways (Miller and Chester, 2016), it is essential that assessments of vulnerability examine the multiple factors that contribute not only to infrastructure shortfalls, but also to the hardship of households during crises. Human-centric resilience planning could have prevented or mitigated the mass damages and inequitable impact that mass rolling power outages had on different communities throughout Texas and other regions impacted by natural disasters.

Gap 4: Digital Divide in Disaster Communication

Information retrieval is a robust determining factor of decision-making at an individual level. In the modern era, much of our information is processed and shared over digital devices. Different social groups have different abilities to generate, disseminate, and use information and access, process, and act on it (Viswanath., 2006; Olteanu et al., 2019; Mislove et al, 2011). Digital trace data has been used to develop indicators of disaster impact disparities (Samuels & Taylor, 2019; Meyer, 2020), which have led to potentially discriminatory decisions (Olteanu et al., 2019), disparities in in emergency response and protection of disaster victims (Vaughn and Tinker, 2009), and distortion population needs (Xiao et al., 2015). Existing disparities among vulnerable groups can be exacerbated by differences in social media access and use as tools for disaster and service disruption communications. However, previous studies have not investigated the role of infrastructure service disruptions in communication behaviors, and similarly, how households use digital platforms like social media, to cope with service disruptions.

RESEARCH OBJECTIVES

The overarching objective of this dissertation is to transform the current understanding of the underlying dynamics that influence risk disparities in vulnerable population groups due to infrastructure service disruptions. It is proposed that if the differential nature of household vulnerability to disruption impacts can be quantified, then stakeholders can more effectively address the root causes of disparity and build more resilient communities before a disaster strikes. Therefore, this **research aims to empirically assess the extent to which different social subpopulation groups are impacted by service disruptions differently through: (1) exposure to disasters, (2) well-being assessments, and (3) pre-existing household characteristics and conditions. The targeted objectives are the following:**

Objective 1: Identify the differential factors of infrastructure service disruption risk impact (digital divide, protective actions, household characteristics) in households during disasters.

Objective 2: Develop empirical-based models that can broaden our understanding of infrastructure system – human interactions for informing equitable and resilient infrastructure prioritization and planning.

RESEARCH QUESTIONS

To address the gaps in knowledge regarding household-infrastructure system interactions and to achieve the specified research objectives, the following questions serve as the pillars of the research:

RQ 1: To what extent do infrastructure disruptions impact the well-being of households differently? Is the impact homogenous across different services and population groups?

RQ 2: How do pre-existing household characteristics, protective action behaviors, and the built-environment collectively contribute to the vulnerability of households sheltering-in-place to well-being impacts due to infrastructure service disruptions?

RQ 3: What are the pathways to well-being impact across population groups and services? Which population groups and well-being risk factors should be prioritized in hazard mitigation planning and infrastructure resilience modeling?

THEORETICAL FRAMEWORK

This dissertation builds on the constructs of the Protective Action Decision Model (Lindell & Perry, 2011) and theory of Planned Behavior (Ajzen, 1985), Capability Approach, and the Digital Divide (Viswanath, 2007) to develop a suite of frameworks and models that explain the differential risk factors of households during and after disasters and the underlying factors of well-being disparity outcomes because of critical infrastructure service disruptions. Empirical data collected through a series of household-surveys are drawn upon for the statistical analysis performed in this dissertation. **Four studies were designed to address the empirical knowledge**

gaps in our understanding of humans-disaster-infrastructure resilience interactions summarized in this section.

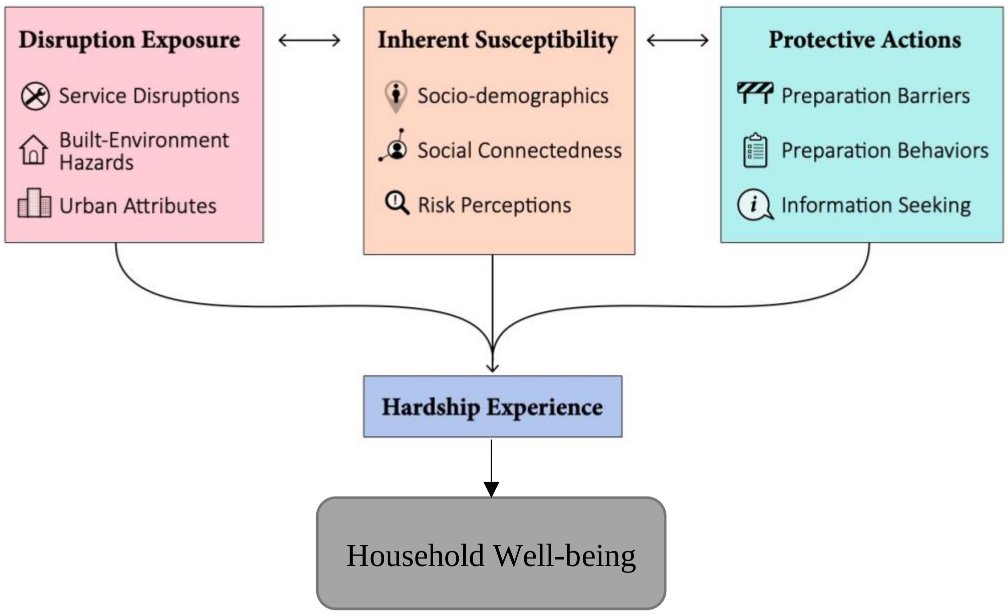


Figure 2: Theoretical Framework

DATA

Empirical data related to households' experiences with infrastructure service disruptions were collected by the Urban Resilience.AI Lab at Texas A&M University starting in 2018 through 2019.The survey was designed and deployed in close collaboration with the Texas A&M Public Policy Research Institute (PPRI). The representative sample was provided by Qualtrics, a survey company that matches respondent panels with demographic quotas. Quotas created from the U.S. Census Bureau data were provided to draw a representative sample from the region based on age, race/ethnicity, and gender. This survey data is used to analyze the factors of well-impact disparities related to critical infrastructure service disruptions during significant hurricane events. Several household surveys were previously deployed to collect relevant service disruption data for different magnitudes and types of hurricane events: Hurricane Harvey, notable for catastrophic flooding; Hurricane Michael, characterized by severe wind damages; and Florence, defined by extreme flooding and wind damages (Fig 3). The household samples focus on shelter-in-place households (those who did not evacuate) to understand the dynamics of infrastructure disruption experiences at the household level. The rationale for this selection was that, for the people who evacuated and had to move to shelters or other places, the relevance of infrastructure service disruptions becomes of secondary importance since they have already lost their shelter (the primary place in which infrastructure services are utilized). The focus of this study was to examine the impacts of infrastructure service disruptions on households; thus, coastal areas with evacuation orders were not included in the samples. As a result, coastal areas and areas with mandatory evacuation orders were not sampled in the survey. The number of respondents for each hurricane focus area was designed to be proportional to the ZIP codes population and for sufficient representation of vulnerable population groups.

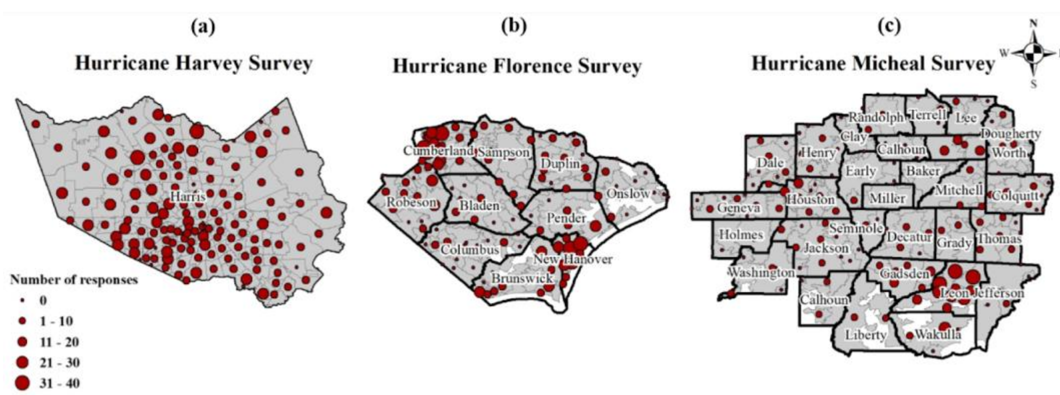


Figure 3: Survey Response distribution over study areas: Harris County (a), North Carolina (b), Georgia, Florida, Alabama (c).

RESEARCH APPROACH

This study follows a multiple-journal paper format developed to advance our understanding of human-centric household factors that influence hardship outcomes due to service disruptions during disasters through four related studies. Chapters 2 through 5 represent research articles that have been published or are in the review process of peer-reviewed journals recognized in the fields of disaster science research, infrastructure resilience, and sustainability. The results of each study aim to address the overarching research questions and objectives as depicted in Figure 3.

Chapter II: Study 1 - Well-being Disparities Due to Service Disruptions

Well-being as a construct depends on the interconnection and feedback between physical infrastructure and individuals' ability to adapt to disruptions (Doorn et al., 2018). High states of well-being have been associated with greater resilience to the impacts of disasters and faster recovery. States of emotional or mental well-being are critical determinants of one's ability to cope with the everyday stresses of life (WHO, 2001; Institute of Medicine, 2015), particularly the stresses induced by disasters (Dargin et al, 2020). In this study, the conceptual model for assessing well-being relationships between households and infrastructure systems and a method for measuring disparity in well-being impact due to service gaps. This study investigates the effects of disruptions in electricity, water, transportation, food, and communications and how they impact the household well-being of different subgroups using a case study of Houston households surrounding Hurricane Harvey. Empirical data collected by means of a household survey is used to examine the influences of sociodemographic household-level factors empirically and systematically. Accordingly, the characterization of service gaps will be used to explain why and to what extent infrastructure service disruptions influence different subpopulations. The purpose of the study is, thus, to advance the understanding of household network dynamics and integrate human- centric considerations into prioritizing and planning of equitable resilient infrastructure and break new ground in our understanding of risk disparity (i.e., social inequality in risk impacts) due to service disruptions. This chapter is co-authored with Dr. Ali Mostafavi and was published in *The International Journal of Disaster Risk Reduction* (Dargin and Mostafavi, 2020a).

Chapter III: Study 2 - Digital Divide and Infrastructure Resilience

The Protective Action Decision Model explains how individuals and household prepare and respond to disaster events, where information retrieval is a robust determining factor of decision-making at an individual level. In the modern era, much of our information is processed and shared over digital devices. The Digital Divide, explored in Study 2, is used to understand how the cycle of information sharing and retrieving factors into well-being impact disparities. This understanding helps us understand whether the digital divide influences how households experience service disruptions differently. This study investigates the role of the digital divide in social media use and platforms in disaster risk communications. This paper presents an exploratory analysis of empirical household survey data on the information seeking, sharing activity, and perceptions of information reliability on social media platforms across different population groups during three major hurricane storm events in the United States between 2017 and 2018. The results of this analysis suggest significant associations between social media use and socioeconomic factors: (1) Socioeconomic factors along with geographic effects play a role in determining not only platform uptake but both motivations for information seeking and the action of information sharing on social media, (2) The type of social media platform influences the type of information people seek, (3) House- holds from lower socioeconomic and minority backgrounds were more likely to seek out different information on social media from their peers, (4) perceptions of information reliability are also influenced by social divides, where households in rural areas, lower income groups, and racial minorities were more likely to report greater unreliability in social media information. These findings provide new insights into the roles of social media use in creating or dismantling the digital divide during disasters. This chapter is co-authored with Dr. Ali Mostafavi and was published in *The International Journal of Disaster Risk Reduction* (Dargin and Mostafavi, 2020b).

Chapter IV: Study 3 - Integrated Service Disruptions During Disasters

The connection between well-being and infrastructure disruptions is supported by the capability approach framework, which relates to providing resources and an enhanced state of well-being (Sangha et al., 2015). For example, an infrastructure system can provide households with essential services that enable specific tasks or activities to occur (jobs, school), with the underlying goal to maintain or improve well-being. This chapter consists of Study 2, which presents the models for assessing food-energy-water nexus interactions at the household-level during a disaster. Combining disaster risk theory and Food Energy Water (FEW) Nexus systems thinking, this study develops a new framework to analyze the collective influence of integrated infrastructure disruptions and socioeconomic factors on household vulnerability during Hurricane Harvey. ANOVA one-way tests are used to determine the disparity in disaster risk measures across non-vulnerable and highly vulnerable households. Structural Equation Modeling (SEM) is employed to test the proposed associative pathways between infrastructure disruptions, urban attributes, household preparation behaviors. The results of the model intend to specify the effects of infrastructure disruptions on households' access and consumption of FEW resources and inform about the household-level attributes and behaviors that shape the demand and access to FEW resources in the context of natural hazards. In doing so, the model can address existing gaps in our understanding of FEW nexus system interactions and vulnerabilities at the household level. This chapter is co-authored with Dr. Ali Mostafavi and was published in *Sustainable Cities and Society* (Dargin and Mostafavi, 2020c).

Chapter V: Study 4 - Differential Pathways of Well-being Disparity in vulnerable groups and different infrastructure services

Study 4 culminates this dissertation work by integrating the findings of the previous three studies. In this chapter, Classification and Regression Trees (CART) is used to map the differential pathways of well-being impact across vulnerable population groups and infrastructure services. The objective of this study is to empirically and systematically assess the combination of inherent susceptibility factors, protective actions, and factors of hazard exposure that influence a household's level of hardship experienced due to disruptions in critical infrastructure services during disasters. The results reveal how the associative pathways between these factors change between socioeconomic and demographic groups in the impacted community and for different infrastructure service system types. The findings suggest that not all vulnerable households experienced high hardship outcomes despite prolonged outages. Finally, the hardship pathways suggest recommendations for improving resilience in infrastructure systems in a more equitable manner. The findings can be used by emergency and infrastructure managers and operators to better prioritize resource allocation for hazard mitigation investments and restorations. Accordingly, this study contributes to the theory of human-centric infrastructure resilience. The chapter has been submitted to a peer-reviewed journal and is under-review now.

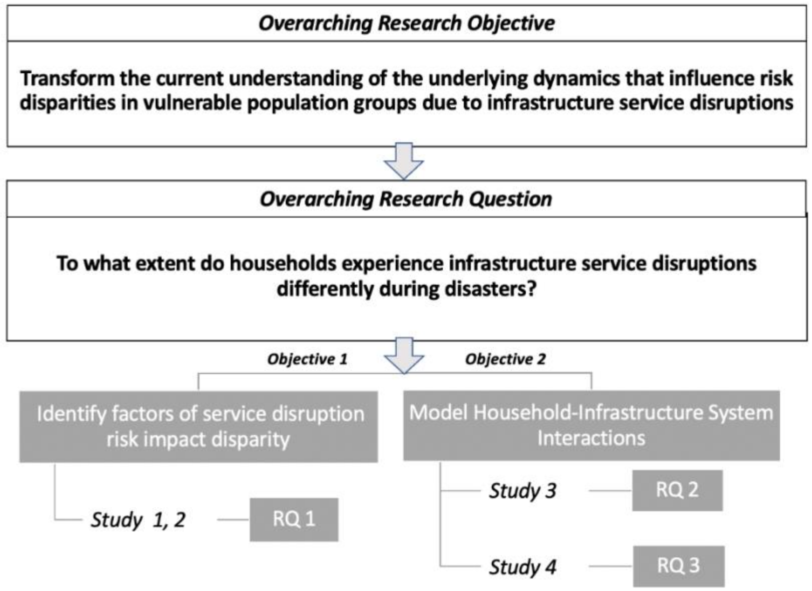


Figure 4: Dissertation Structure

CHAPTER II: STUDY 1 - HUMAN-CENTRIC INFRASTRUCTURE RESILIENCE: UNCOVERING WELL-BEING RISK DISPARITY DUE TO INFRASTRUCTURE DISRUPTIONS IN DISASTERS †

OVERVIEW

The objective of this paper is to empirically examine the impacts of infrastructure service disruptions on the well-being of vulnerable populations during disasters. There are limited studies that empirically evaluate the extent to which disruptions in infrastructure system services impact subpopulation groups differently and how these impacts relate to the wellbeing of households. Being able to systematically capture the differential experiences of sub-populations in a community due to infrastructure disruptions is necessary to highlight the differential needs and inequities that households have. In order to address this knowledge gap, this study derives an empirical relationship between sociodemographic factors of households and their subjective well-being impacts due to disruptions in various infrastructure services during and immediately after Hurricane Harvey. Statistical analysis driven by spearman- rank order correlations and fisher-z tests indicated significant disparities in well-being due to service disruptions among vulnerable population groups. The characterization of subjective well-being is used to explain to what extent infrastructure service disruptions influence different subpopulations. The results show that: (1) disruptions in transportation, solid waste, food, and water infrastructure services resulted in more significant well-being impact disparities as compared to electricity and communication services;

[†] This chapter was submitted to "PLoS ONE" journal as an individual paper (Dargin, JS and Mostafavi, A (2020). "Human-centric infrastructure resilience: Uncovering well-being risk disparity due to infrastructure disruptions in disasters." *PLoS ONE 15(6): e0234381. https://doi.org/10.1371/journal. pone.0234381*

(2) households identifying as Black and African American experienced well-being impact due to disruptions in food, transportation, and solid waste services; and (3) households were more likely to feel helpless, difficulty doing daily tasks and feeling distance from their community as a result of service disruptions. The findings present novel insights into understanding the role of infrastructure resilience in household well-being and highlights why it is so important to use approaches that consider various factors. Infrastructure resilience models tend to be monolithic. The results provide empirical and quantitative evidence of the inequalities in well-being impacts across various sub-populations. The research approach and findings enable a paradigm shift towards a more human-centric approach to infrastructure resilience.

INTRODUCTION

The impact of natural disasters is often measured by a handful of numbers: the number of fatalities and injuries, the number of homes and buildings destroyed, and the cost of cleanup and repair. However, these measures do not often account for the emotional wounds inflicted on survivors. Furthermore, infrastructure resilience planning needs metrics that are "precise" for measuring both individual system qualities and generalizable in order to inform resource allocations and operations (Rand et. al, 2020; Linkov et al., 2014). Subjective well-being, defined as 'a person's cognitive and affective evaluations of his or her life,'(Diener, 2002) as a human-centric measure of infrastructure resilience allows us to diverge from these standard assessment measures used in evaluating societal impacts of critical infrastructure service disruptions during disasters.

Time and again, natural disasters have tested the resiliency of both built infrastructure and communities. Disruptions in infrastructure services caused by natural disasters have shown to have significant impacts on the well-being of those affected (Norris et.al, 2002; Ursano et. al, 2007; Shear et.al, 2011; Chang, 2016). Not only that, but they also cause disproportionate impacts amongst communities and that vulnerability is differential; different people and communities are vulnerable in different ways to different hazards (Chang, 2016). An increasing number of studies in the disaster literature have focused on the construct of well- being as a central factor in community resilience for (Brown & Westaway, 2011; Baggio & Colliard, 2017; Kellezi et. al, 2008; Laurence et.al, 2009; Nyanmwanza, 2012; Uchida et.al, 2014; Capic et.al, 2016; Badland et.al, 2014). However, these studies did not analyze how well-being experience differentiated according to household sociodemographic characteristics as a result of infrastructure disruptions.

Considering the complexity of modern critical infrastructure systems in terms of its inter-dependencies and external pressures, including increasing demand, aging, and climate change, the risk and severity of disruptions are becoming more likely. Community resilience planning is tasked with ensuring the equitable access and delivery of critical infrastructure system ser- vices in cities by reducing the disproportionate risks of service disruptions to the most vulnerable members in a community. However, as our infrastructure systems become "smarter" with the ability to capture more data and make decisions, resilience plans may become less in touch with the individuals and households for whom the resilience strategies exist (Chang, 2016). Infrastructure and technology-centric approaches generally fail to provide visibility into emergencies caused by infrastructure disruptions in disasters (Chang, 2016). Likewise, such approaches assume communities of households to be monolithic and are unable to capture the diversity of household characteristics that influence their resilience in the face of disaster (Chang, 2016).

Few empirical studies have focused on the resilience of small groups or units, such as house- holds (Zemba et. al, 2019). The lack of fundamental information about household interactions with infrastructure services in disasters, and more specifically, how these interactions differ with respect to different population attributes. Understanding the disparities in infrastructure disruption impact is key to integrating the needs of diverse populations into planning and prioritization of resilient infrastructure while mitigating impacts to the most vulnerable members of society when infrastructure services are disrupted.

A human-centric approach to infrastructure planning and management is a shift away from conventional engineering approaches which generally focus on the performance and physical failures within systems. From a perspective of resiliency, more focus needs to be directed towards how infrastructure systems make residents feel and whether or not there is an equitable provision of infrastructure services to the community. Having this focus is particularly important in times of disasters where service disruptions can negatively affect human well-being. To address these shortcomings, this paper presents a human-centered approach to empirically analyze the relationships between households and critical infrastructure service disruptions by examining the extent to which disruptions in various infrastructure (e.g., transportation, power, water, and communication) would affect different aspects of well-being (i.e. social and emotional) for different sub-population groups. The results from this analysis aim to emphasize the importance of including different community perspectives and needs in infrastructure resilience planning by providing empirical evidence of impact disparities. Achieving these objectives is critical for advancing the understanding of household network dynamics and integrating human-centric considerations into prioritizing and planning of equitable resilient infrastructure.

RESEARCH SCOPE

A set of human-centric variables (i.e., *measures of social and emotional well-being*) are drawn upon from the Personal Wellbeing Index (PWI) (International Wellbeing Group, 2013) to derive an empirical relationship between sociodemographic factors of households and their subjective experience with disruptions in critical infrastructure services during and immediately after Hurricane Harvey. Over- all, the research aims to form the basis of an empirical relationship between human and infrastructure systems while characterizing household-level disparities in impacts due to ser- vice disruptions. Households have been selected as the unit of analysis as they are the unit in which network interactions between humans and infrastructure services occur. Accordingly, the characterization of well-being is used to explain the extent to which infrastructure service disruptions influence households differently according to their differential household sociodemographic attributes. This research presents a novel attempt to understanding the role of infrastructure resilience in household well-being outcomes during crisis situations, as well as inequalities in disruption impacts according to different household attributes. More specifically, the analysis is guided by the following research questions:

RQ1: Do infrastructure-disruptions influence well-being impacts in households? If so, what services have the most impacts and on which well-being dimension?

RQ2: Are there disparities among households with vulnerable population groups in terms of well-being impacts caused by infrastructure service disruptions? If so, what sub-populations experience disproportionate well-being impacts for different service disruptions?

To address these questions, a new framework for a human-centric infrastructure service model that conceptualizes the association between humans (in terms of well-being) and infra- structure (in terms of service provisions) is introduced. Secondly, an approach to determining disparities in well-being impacts due to different service disruptions at the household level is discussed and demonstrated using empirical data collected from a household survey and analyzed using correlation analysis. The remainder of this section discusses the knowledge gaps to highlight the point of departure and significance of this study further.

LITERATURE REVIEW

State of Infrastructure Resilience Approaches

Resilience is “the ability to plan and prepare for, absorb, recover from, and adapt to adverse events” (NRC, 2012). The goal of infrastructure resilience approaches and analysis is to mitigate negative impacts while ensuring that the “targeted system rebounds to full functionality as quickly and efficiently as possible” (Linkov & Palma-Oliveira, 2017). Societal determinants of risk can be used in resilience models and planning to achieve better economic and social development trajectories (Falco, 2015; Aitsi-Selmi et.al, 2015). Agent-based models have been applied to incorporate complex social measures and household characteristics into infrastructure resilience modeling (Miles, 2015; Esmalian et. al, 2019; Rasoulkhani & Mostafavi, 2018; Bruneau et. al, 2003). Methods and tools that do incorporate social considerations for modeling the resilience of infrastructure systems (Doorn et al., 2018; Nateghi et. al, 2011) either only focus on single dimensions of resilience from a technical standpoint or model the various dimensions separately (Nateghi et. al, 2011). They are further limited by narrow outlooks on the service population, neglecting various household-level attributes that might influence the service quality experience across different households. In order for resilience planning and risk reduction planning processes in infrastructure systems to consider societal dimensions of service disruptions, it is essential to understand the human well-being impacts. Disaster impact on humans has been studied from economic, psychological, and physical health perspectives. However, such studies do not entirely focus on infra- structure systems or their services and do not capture the impact of disaster-inflicted service outages on households sheltering in place. Hence, empirical research such as the work presented in this paper is necessary for determining appropriate community resilience metrics that account for the interaction between society and built infrastructure (Bruneau et. al, 2003).

Gaps in Research

The role of infrastructure systems and the services they provide in community resilience and the importance of understanding and reducing disruption impacts have been established by interdisciplinary fields (Siamak et. al, 2018; NRC, 2012; NIST, 2016). Measuring the impact of infrastructure services on human well-being and the extent of risk and uncertainty involved in the operations of infrastructure systems is imperative for creating both resilient infrastructure and communities (NRC, 2013; Haines & Kovats, 2006). More particularly, the need to know how to integrate the needs of diverse populations in planning and prioritization of resilient infrastructure. This knowledge will help to improve social inequities, and as a result, foster more resilient communities. It then becomes clear that there is a need for human-centric approaches to infrastructure resilience planning and modeling. Until now, socioeconomic measures that are typically used in studies rely on GDP, mortality rates, and patient data, which are not sufficient in capturing the differential well-being of shelter-in- place households before and during disasters. Disaster research has been able to at a high level, identify that minority groups are more prone to the impacts of disasters. However, the research does not explicitly relate these outcomes to the infrastructure systems that enable them nor specify the influence of infrastructure disruptions on the well-being of these vulnerable groups. Very few, if any, infrastructure resilience or disaster recovery models exist that rep- resent variables of community well-being or public health (Mostafavi & Ganapati, 2018). This limitation is mainly due to the lack of empirical information that specifies the relationship between infrastructure disruptions and various elements of human well-being for different sub-populations. A couple of studies (Guan & Chen, 2016; Barrett et.al, 2012) have used network analysis and social media data to examine changes in transportation and wireless infrastructure systems in the context of disasters. Song et al. (2018) developed a resilience model to measure the resilience level of different areas during typhoons based on social, economic, infrastructural, and natural components. This study did not, how- ever, look at a direct relationship between infrastructure disruptions and household impacts. Román et al. (2019) used spatial analysis to track outages and recovery times of power infrastructure during Hurricane Maria and linked these measures to census-based demo- graphic characteristics of residents. Similarly, this study focuses on a single infrastructure system.

Well-being as a Measure for Minimizing Social Inequality in Disaster Risks

Disasters have long-term and serious effects on the emotional and social wellbeing of the populations impacted (Institute of Medicine, 2015). Additionally, higher levels of well-being have been shown to be an indicator of greater resilience to disaster impacts and the ability to recover. In order to increase levels of societal and individual wellbeing, there needs to be a reduction in socioeconomic inequalities (Pampel et.al, 2010; Kelly & Evans, 2017; OECD, 2013). If the underlying purpose of human-centered approaches to infrastructure resilience is to improve social equity in communities, then appropriate measures need to be adapted. Measures of societal progress need to be able to understand the diverse experiences and living conditions of people (UNDRR). Existing protocol, standards, and guidelines for engineering performance governing infrastructure design rarely include the socioeconomic impacts of infrastructure service disruption. Often, measures of social impacts of disaster typically attempt to quantify the impact in terms of economic loss (Cheng, 2016), mortality, or medical cases (UNDRR). For example, Burrus et al.

(2002) and Santos et al., (2014) understand workforce recovery and how it couples with critical infrastructure availability. Such measures, however, do not provide sufficient assessment of the living conditions that people in communities experience.

In the context of infrastructure resilience and disaster, measuring subjective well-being in and of itself can draw more attention to the needs of different sub-populations within a city and towards potential action-oriented solutions [45]. In fact, integrating measures of well- being in infrastructure resilience assessments can shift the focus from "systems" to "people." Several countries and cities have already started working in this space, measuring subjective well-being households in official statistics that are intended to drive policy decisions [46] and to assess and inform public policy and other action plans [42,47–49]. Nevertheless, the current resilience planning and risk reduction processes in infrastructure systems have yet to adopt measures of well-being to inform investment, resource allocation, and prioritization decisions and policies.

Vulnerable Populations and Resilience

During and after disasters, "vulnerable populations require more assistance and are the least capable of taking care of themselves and generally live in the oldest and most hazardous buildings" [30]. Variations in socio-demographic attributes, access to resources, expectations, and norms cause specific households to endure more significant impacts as a result of infrastructure disruptions during and after a storm. Isolating vulnerable persons during and following a disaster event actually creates an increased *dependency burden* on infrastructure services when it is least afforded [50]. Numerous studies have clarified the heightened vulnerability of population groups such as the elderly, children, linguistic minorities [51]. and low-income house- holds during and in the aftermath of a disaster event. Research over the last several years [52– 53] has analyzed the social impacts of transportation disruptions following severe weather events based on measures of accessibility. While the studies were distributed across different geographic areas and urban settings, all concluded that impacts on the communities differed demographically (Cheng, 2016). Studies have shown that racial and ethnic minorities are less likely to evacuate in times of disasters (Cheng, 2016; Stough & Kang, 2015; Few & Matthies, 2013) and more likely to live in areas predisposed to environmental hazards and risks (Hajat et al., 2007). Studies have shown that particular age group populations are also disproportionately exposed to weather-related hazards (Kovats, 2009; Silverman & La Greca, 2002; Lin et al., 2016). Silverman and La Greca (2002) studied the impact that children experience during and after a disaster. Based on their findings, the community outcome of a disaster generally show that minority youth have a greater chance of reporting high levels of PTSD symptoms; this then leads to their conclusion of minority youth having a much more difficult time recovering than those of non-minority youth. During Hurricane Sandy, researchers found that power outages had different mental health impacts of counties and individuals of lower socioeconomic status (Sen, 1985). These studies suggest the importance of an evaluation of disparities in well-being impacts for vulnerable subpopulations exposed to infrastructure service disruptions.

CONCEPTUAL FRAMEWORK

This paper proposes an infrastructure resilience and well-being disparity framework (Fig 1) to conceptualize the association between humans (in terms of well-being) and infrastructure (in terms of service provisions). The connection between well-being and infrastructure disruptions are supported by the capability approach framework (Sangha et al., 2015). According to Sen's capability approach, the provision of resources enables people to develop capabilities that help them achieve 'functioning's,' or in other words, an enhanced state of well-being (WHO, 2001).

We use this idea to bridge the measures of hardship experience due to infrastructure disruption and well-being. In this context, the infrastructure system aims to provide households with services that enable them to develop or do specific tasks (jobs, school), with the underlying goal to maintain or improve well-being. This approach is suitable for expressing non-tangible damage caused by natural hazards and disasters, such as the subjective experiences of individuals and households.

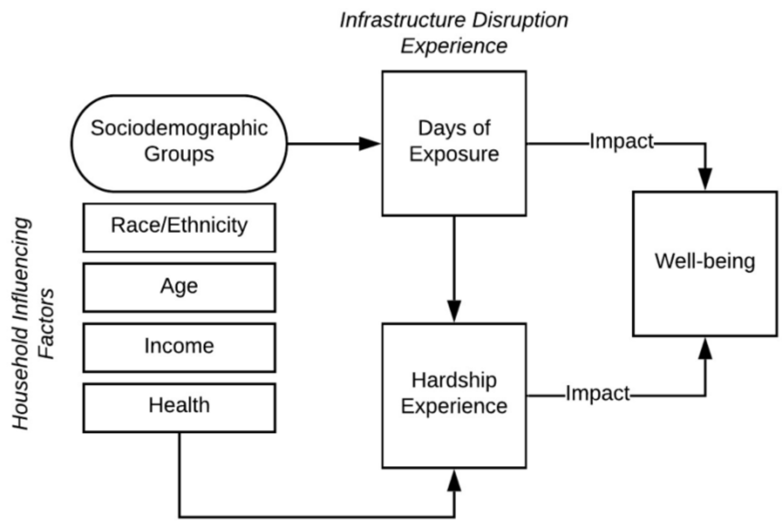


Figure 5: Infrastructure resilience and well-being framework

Fig 5 presents the conceptual model of infrastructure resilience and household well-being disparity. The framework summarizes and relates two components (households and infra-structure) using three constructs (well-being, sociodemographic characteristics, and infra-structure services). In this framework, household well-being (in relation to infrastructure) is determined based on two elements: (1) the extent of service disruptions (days of exposure to service outages, and (2) the extent of hardship experience due to service disruptions. The extent of hardship is used as an indicator for examining the nature of experience related to a service disruption. A household's hardship experience is influenced by various factors such the socio-economic characteristics, preparedness, and access to resources. In this study, only sociodemographic characteristics are considered since the goal of the analysis is to examine the presence and extent of disparities in well-being impacts among various sub-populations. This section here on out defines the variables and pathways depicted in Fig 5.

Well-being as a Human-Centric Component

According to Doorn et al. (2018), societal well-being depends on the interconnection and feedback between physical infrastructure and the ability of individuals to adapt to disruptions. Disasters have long-term and serious effects on the emotional and social wellbeing of the populations impacted (NRC, 2013). Additionally, elevated states of well-being have been associated with greater resilience to disaster impacts and the ability of communities to recover. States of emotional or mental well-being, which are key determinants of one's ability to cope with the nor- mal stresses of life (WHO, 2001; Institute of Medicine, 2015), and in particular, the stresses induced by disasters. Therefore, it is the social and emotional aspects of well-being that are emphasized and analyzed with the presented framework. This framework defines the onset of a disaster event and the resulting infra- structure disruptions as extrinsic factors that have the potential to influence a household's level of well-being. Self-reported subjective well-being impact measures are drawn upon from existing well-being and mental health, a component of well-being, assessments to quantify the social and emotional well-being of households within one month of Hurricane Harvey. These measures are presented and discussed in the proceeding section (Table 1).

Given the interdependencies of modern lifestyles and infrastructure services as addressed in the previous section, it is then apparent how lack of service or diminished quality in service can impact the well-being states of people. The impact of a natural disaster is often measured by a handful of numbers: the number of fatalities and injuries, the number of homes and buildings destroyed, the cost of cleanup and repair. It does not often account for the emotional wounds inflicted on survivors. Well-being as a human-centric measure of infrastructure resilience allows us to diverge from these standard assessment measures used in evaluating societal impacts. While the self-reported well-being measures examined in this study can be indicators of actual mental illness (clinical depression), the purpose is not to identify whether or not there are more incident cases of mental illness.

Infrastructure Service Hardship Experience

Critical infrastructure includes systems and assets, which in the event of incapacity or destruction, would have a debilitating impact on the functioning of society from a perspective of public health, national security, and economic security (NIST, 2016). While there are 16 infrastructure systems deemed critical by the federal government, research tends to focus on just five of them: energy (particularly electric power), water, wastewater, transportation, and telecommunications systems. Food and solid waste services are not typically included in research involving critical infrastructure systems even though the significant and long-lasting damages disasters have caused to them in the past and potential public health hazards they can create (Brown et al., 2011; Suleman & Agyemang-Duah, 2015; Martuzzi et al., 2010; Mohai & Saha, 2015). Disadvantaged communities often suffer disproportionately from the impact of waste facilities (Mohai & Saha, 2015) and racial minorities are more likely to live in closer proximity to waste facilities (Mohai & Saha, 2015). Access to food retailers becomes limited due to disruptions in other supporting critical infrastructure systems, including electricity, potable water, and transportation (Nozhati et al., 2018).

Table 1: Adapted measures for well-being impact assessment

Well-being Measure	Survey Question
Helplessness	How often did you find yourself or a household member helpless (one month after Hurricane Harvey)?
Anxiousness	How often did you or a household member feel anxious, worried or nervous (one month after Hurricane Harvey)?
Upsetting thoughts	How often did you or a household member have upsetting thoughts and feelings related to the storm or the damage it caused (one month after Hurricane Harvey)?
Safety	How much did your household, experience with Hurricane Harvey make you or members of your household feel less safe and protected in your daily life (one month after Hurricane Harvey)?
Depression	How much did your household experience with Hurricane Harvey make you or members of your household feel depressed or restless (one month after Hurricane Harvey)?
Daily life tasks	How much did your household, experience with Hurricane Harvey lower your ability to do your daily life tasks such as working or dealing with others (one month after Hurricane Harvey)?
Feeling distant	How much did your household, experience with Hurricane Harvey make you or members of your household feel distant or cut off from other people (one month after Hurricane Harvey)

Similarly, vulnerable populations such as children, the elderly, ethnic minorities, and low-income house- holds are disproportionately affected by food security (RTI International, 2014; Rose et al., 2011). During Hurricane Katrina, access to supermarkets declined for all census tract neighborhoods but was primarily limited for African American tracts, which 71 percent less likely to have access to a new supermarket (Blunt, 2017). In the case of Hurricane Harvey, disruptions to foodservice systems (broken refrigeration units and supply chains) led to the expansion of urban food deserts. To remedy the disruption in food availability and access, the Supplemental Nutrition Assistance Program (SNAP), was expanded to nearly 600,000 households affected by the storm (Wolbring Keuschnigg, 2011).

In socioeconomic research, economic hardship has been shown to thwart well-being in households and individuals (Reeskens & Vandecasteele, 2017; CDC, 2018; Juntunen, 2005). Based on this assumption supported by theoretical research, it is proposed that hardship experience due to infrastructure disruptions also impacts household well-being. Hence, in this study, we use hardship as a proxy variable for determining the relationship between well-being and infrastructure service disruptions. Disparities among sociodemographic groups are often studied in public health and epidemiological research in the context of health equity and are defined as occurring when a population group has a disproportionate share of health burden (Flanagan et al., 2011). The *infrastructure resilience and well-being disparity model* applies the same concept and definition of disparity: when one subgroup population has disproportionate experience in well-being impact as a result of the exposure and experience with infrastructure service disruptions. The higher impact of infrastructure disruption experience indicates a more significant negative well-being impact.

Days of Exposure

In Esmalian et al. (2019), the authors found no significant disparity in days of exposure to hardship experience across various subgroups for electricity services in Hurricane Harvey. This finding indicates that exposure to service disruptions was not significant for different socio-demographic groups. For that reason, we do not link days of exposure to sociodemographic factors. Furthermore, the study found a positive correlation between days of exposure to hardship experience. Hardship experience is used as a proxy variable of infrastructure disruption experience to draw a connection to well-being experience. The household influencing factors only focus on sociodemographic groups so that we can analyze whether or not sociodemographic play a role in well-being experience. Sociodemographic characteristics are hypothesized to influence the extent of hardship experienced, which is also determined by the days of exposure. On the other hand, as the households experienced more service losses (more days of a power outage), they experience more hardship as shown by the positive correlation between the interruption and self- reported hardship. However, we hypothesize the sensitivity of hardship experience (and the subsequent well-being impacts) to the duration of service disruption varies for different sub-populations and various infrastructure services.

Household Factors Influencing Disparity

Social vulnerability in the context of disaster management emerged from the realization that socioeconomic factors affect community resilience (Juntunen, 2005). In disaster events, infrastructure disruptions frequently cause or exacerbate many types of socioeconomic impacts, including health, social, economic, and environmental consequences (Cheng, 2016). Vulnerable populations referred to in this framework have been derived from the Social Vulnerability Index (SVI) (CDC, 2018) and include households who are racial or ethnic minorities, children, elderly, socioeconomically disadvantaged, underinsured or those with certain medical conditions. SVI was developed to assist in disaster planning and public health practitioners in identifying high-risk communities during hazards or recovering from disasters (Flanagan et al., 2011). It uses U.S. Census Bureau data to determine the social vulnerability at tract-level based on 15 social factors grouped by four related themes: Socioeconomic status, Household Composition/ Disability, Minority Status/Language, Housing/Transportation (Flanagan et al., 2011). While sociodemographic factors influence the extent of hardship, and ultimately the well-being experienced, it is recognized that life events (i.e., disasters and changes to critical infrastructure services) have the potential to be detrimental to health and well-being (Cleland et al., 2016).

MATERIALS AND METHODS

This research was approved by Texas A&M University IRB: IRB2018-0459M. No consent was obtained because the data were analyzed anonymously. The study is centered around the critical infrastructure outages affecting Harris County residents during Hurricane Harvey. Hurricane Harvey was a Category 4 storm that made landfall in Texas on August 25th, 2017.

Harvey led to severe rainfall and mass flooding throughout the state. The proposed well-being frame- work is used to identify areas of risk disparity due to infrastructure service disruptions within a population. The survey design, data measures, and analytical approach are described. More- over, we utilize empirical data from Hurricane Harvey to test the proposed framework in answering the proposed research questions in the context of critical infrastructure system disruptions due to disaster.

Survey Design

Hurricane Harvey made landfall on Texas in late August 2017, impacting all 4.7 million inhabitants of Harris County, the most populous county in Houston and in Texas. Record-breaking rainfall wreaked havoc on Houston's infrastructure systems and households making it one of the costliest disasters in U.S. History, after Hurricane Katrina. All 22 of Houston metro's major freeways were flooded and impassable during the storm while nearly 300,000 house- holds lost power (HCFCD, 2018). Empirical data were collected from households in Harris Country, Texas to gather information on household exposures to infrastructure gaps, hardship experiences due to infrastructure service disruptions, and changes to well-being states as a result of the disaster experience according to race/ethnicity, age, socioeconomic status, pre-existing health conditions (disability, chronic health). Questions measuring well-being impact focused on experienced or "hedonic" well-being (Boehm & Kubzansky, 2012). A web-based survey was deployed between April and May 2018 through Qualtrics, a survey company that matches respondent panels with demographic quotas. In order to represent the vulnerable population groups in the study area, the authors provided quotas created from U.S. Census Bureau data to draw a sample from Harris County based on age, race/ethnicity, income, and health status. All participants in the survey were required to be of age 18 years or older. 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 the complete data collection. The purpose of the data was to high- light the trends in vulnerable population group experiences with infrastructure disruptions during a disaster event. As suggested by Lindell (2008), the degree to which sample means and proportions are representative of the study area population is less important than having enough demographic diversity to provide an adequate test of the relationships in the presented correlation analysis. A total of 1081 household samples were collected from 140 of the 145 zip codes in Harris County (Fig 6) According to power analysis, this is a sufficient number of responses to conduct inferential statistics that systematically examine associations within the survey data. Those with incomplete responses and those that had evacuated their households before Hurricane Harvey landed were eliminated from the analysis, narrowing the analyzed sample to 837 households. The focus of this research is on households sheltering in place during a disaster; this discretion, therefore, excludes households that evacuated prior to Harvey's landfall. Harris County was selected particularly because mandatory evacuation orders were not issued to its residents. Within Harris County, only one city issued a voluntary evacuation order (WFAA, 2017). Several coastal counties along the Gulf Coast were ordered to evacuate (WFAA, 2017) which

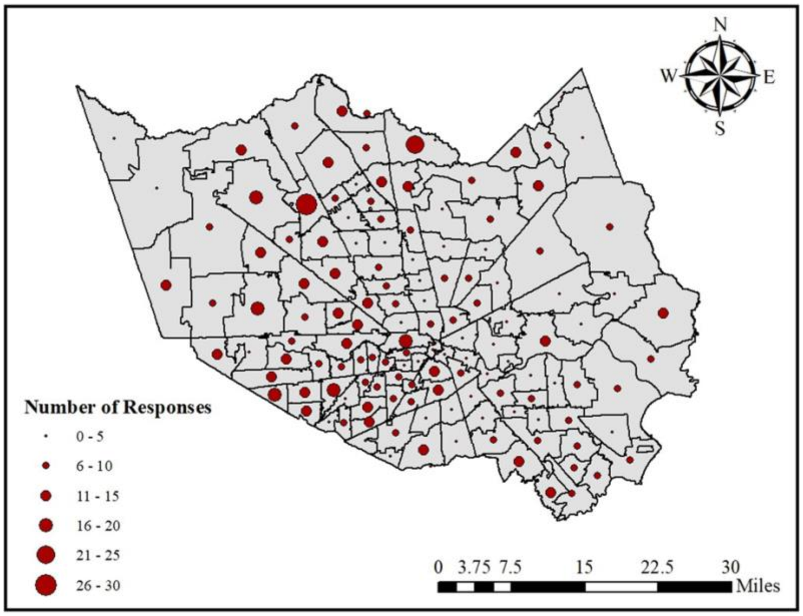


Figure 6: Distribution of households in the study area, Harris County, Texas

would have made these counties inadequate for our study. The rationale for this selection was that, for the people who evacuated and had to move to shelters or other places, the relevance of infrastructure service disruptions becomes of secondary importance since they have already lost their shelter (the primary place in which infrastructure services are utilized).

Data and Measures

This section presents the measures derived from the household dataset that are used as empirical inputs of the proposed infrastructure-well-being framework.

Well-being

This study uses self-reported subjective emotional and social well-being impact measures modified from the Personal Wellbeing Index (PWI) (International Wellbeing Group, 2013) and from a literature review on prominent surveys administered post-disaster that focused on the aspects of social and emotional well-being evaluation of impacted people (Nyamwanza, 2012; Capic et al., 2016; Badland et al., 2014; Schimmack & Oishi, 2005; Michalos, 2010; Foa et al., 2013; Kessler et al., 1996). The PWI focuses on measuring an individual's satisfaction according to a specified set of seven core domains: standard of living, personal health, achieving in life, personal relationships, personal safety, community connectedness, and future security. The domains, *standard of living* and *future security* is not specifically addressed in this study because they do not directly contribute to social and emotional dimensions of well-being that this study primarily focuses on. Additionally, while personal health is one of the domains of the PWI, it does not specifically measure states of emotional or mental well-being, which are key determinants of one's ability to cope with the normal stresses of life (Nyamwanza, 2012), and in particular, the stresses induced by disasters. The authors drew upon the most cited emotional determinants of well-being found in post- disaster mental health assessments: *feeling depressed*, *having upsetting thoughts*, and *feeling anxious*. Furthermore, the inclusion of multiples determinants of emotional well-being will allow the authors to draw connections and determine the aspects of well-being most relevant to disaster experiences and infrastructure disruptions.

Subjective indicators of household well-being are derived from seven survey questions used to measure the social levels of households within one month after the experience of the hurricane event (Table 1). They are self-reported, measured in a five-point Likert-scale ranging from None at all (= 1) to A great deal (= 5). According to the OECD (2013) and standard practice in the psychology field (Schimmack & Oishi, 2005) using multiple items in a scale is preferred so that a broad construct, such as an adverse effect, is measured categorically. The improved reliability of subjective Likert well-being scales as compared with single-item measures, can thus potentially be attributed to their ability to reduce the impact of random error (UNDRR). Table 1 outlines the well- being components included in the final assessment and the survey questions used to collect the measurements.

Hardship

Self-reported hardship due to disruptions in infrastructure services was measured in a five-point Likert-scale ranging from None at all (= 1) to A great deal (= 5) for the following question: Households were asked: "What was the extent of overall hardship experienced due to X outages/interruptions posed by Hurricane Harvey?" Self-reported hard- ship is used as a proxy for examining the experience of households due to service disruptions. The extent of hardship experienced is correlated with both the exposure to disruptions, as well as the socio-demographic characteristics of households. Greater exposure to hardship experiences would lead to more significant well-being impacts. Hence, the combined effects of the extent of hardship experience and the duration of exposure are used to examine well-being impacts on households.

Table 2: Measurement of the influencing sociodemographic factors of household well-being disparities.

Sociodemographic Domains		Survey Measures & Encoding
Age	*Under 10 years*	*Household has child under 10 (Yes (= 1) or No (= 0)*
	between 11–17	*Household has child between 11–17 (Yes (= 1) or No (= 0)*
	Over 65	*Household has elderly resident (Yes (= 1) or No (= 0)*
	Reference group	*Households without children or elderly residents (Yes (= 1) or No (= 0)*
Income	*Low Income*	*$25K - $50K; (= 1)*
	Middle Income	*$55K-$99K; = (2)*
	High Income	*$100K+; (= 3)*
	Reference group	*High Income*
Ethnic Identity	*Black*	*(Black = 1, Non-black = 0),*
	Hispanic/Latino	*(Hispanic/Latino = 1, Non-Hispanics/Latino = 0),*
	Asian	*(Asian = 1, Non-Asian = 0),*
	Other	*(Other = 1, Non-Other = 0),*
	Reference group	*(White = 1, Non-White = 0),*
Health	*Chronic Disease*	*Household has resident with condition: Yes (= 1) or No (= 0)*
	Disability	*Household has resident with condition: Yes (= 1) or No (= 0)*
	Reference group	*No health condition reported: Yes (= 1) or No (= 0)*

https://doi.org/10.1371/journal.pone.0234381.t002

Household Sociodemographic Factors

Household sociodemographic characteristics may describe vulnerable groups that are often at a disadvantage while preparing for, responding to, and recovering from disaster events (Cheng, 2016). For this analysis and to maintain consistency with the elements of social vulnerability index (SVI), households have been classified into subgroups according to reported age groups in the household, ethnic identity, health status, and income level. The survey did not differentiate between white Hispanic and non-white Hispanics. Additionally, the '*other'* racial category represents households that identified as mixed-race or ethnicity in addition to Pacific Islanders and Native Americans. Pacific Islanders and Native American households were grouped into the *Other* category because of the low population samples. Most statistical analyses require sample sizes to be greater than or equal to 10. The income group levels were divided into three brackets (low, middle, high), according to recent census data on median household income in Texas (US Census Bureau, 2018). Sub-categories were combined, as shown in Table 2.

STATISTICAL APPROACH

Identifying reference points is significant for determining disparities across subgroup populations, as their nature cannot be understood unless the point relative to which they are measured is identified (Keppel et al., 2005). A reference point is defined as "the specific value of a rate, percentage, proportion, mean, or other quantitative measures from which a disparity is measured" (Keppel et al., 2005). For *race or ethnicity* subgroups, the reference point has been defined as the group that represents the most substantial proportion of the population (US Department of Health and Human Services, 2010). Disparities can also be measured relative to a standard or target (Keppel et al., 2005). For example, the reference group for income level groups has been determined by the most ideal or favorable income level group (above $100,000). As for health status and age, reference points were determined by households without any reported vulnerable age groups (elderly or children) or health condition (disability or chronic disease). Table 2 summarizes how each sociodemographic factor is measured in the statistical analysis and specifies the reference group for each sociodemographic domain. The set of groups are mutually exclusive and attributed to binary values, apart from income groups which have been encoded as numeric values of 1 through 3, representing low, middle, and high income.

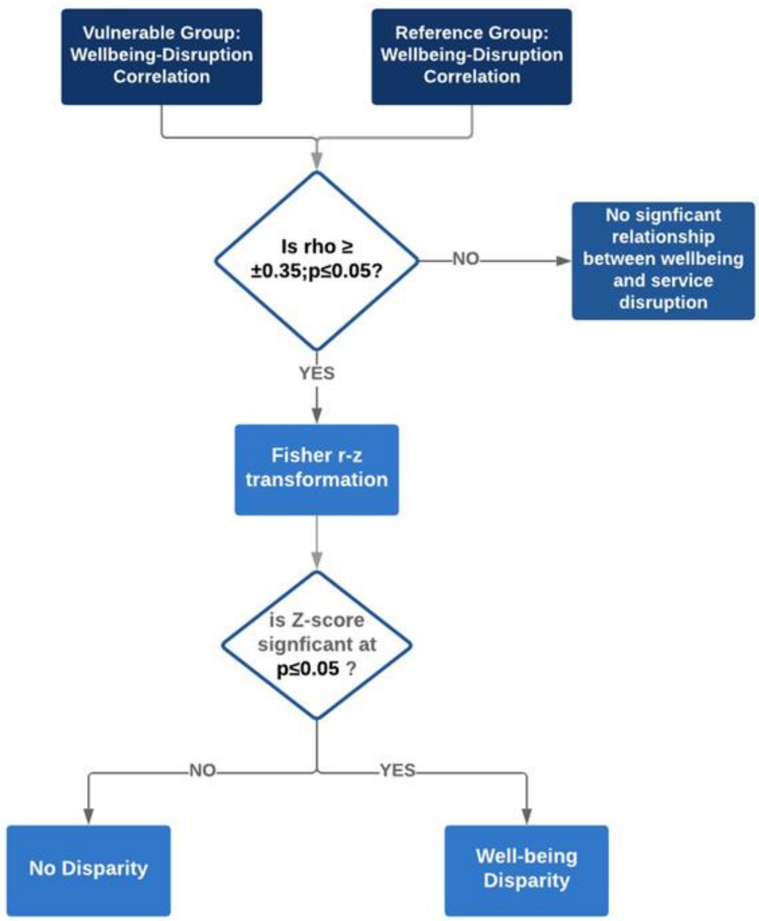


Figure 7: An analytical approach for measuring subgroup well-being disparity

Tests for significance were conducted using the R *cocor package* (Diedenhofen & Musch, 2015). Akoglu, H. (2018) recommends that a specific coefficient should be interpreted as a measure of the strength of the relationship in the context of the posed scientific question, as opposed to clear rules for interpreting coefficient values. Based on the recommendations of literature (Keppel et al., 2005), coefficient values below 0.35 were classified as weak. Correlation coefficients above .35 were considered moderate to high correlation. Trends are identified to characterize services by well-being dimension, and also to identify which subgroup was associated most with which well-being component due to associations with which infrastructure service.

A disparity is determined when there is a significant difference between the coefficient of the vulnerable group and the reference population, and the coefficient is greater than or equal to 0.35, indicating a moderate (either positive or negative) association between well-being impact and infrastructure service disruption (Fig 7). In the context of risk disparities, it is essential to select appropriate metrics to characterize resilience and selection of acceptable risk levels or thresholds. Doorn et al., (2018) suggests that using average values as risk thresholds can be misleading as they can mask important trends and variations within a population sample. Average values were therefore avoided as they may reflect a case in which all individuals had roughly the same impact, or a case in which some individuals were not impacted but a portion of the population was severely impacted (Hinkle, 2003).

RESULTS

The sociodemographic composition of the households represented in the dataset are summarized in Table 3. Since the focus of this research is at the household level, specific information about the individual responders were not collected apart age and county of residence to determine their eligibility for participating in the survey.

Table 3: Sociodemographic characteristics of households in the survey

Household Sociodemographic Identification		Frequency in Survey	% of All Households
Ethnic Identity	White	491	59%
	Hispanic or Latino	95	28%
	Black or African American	160	15%
	Asian	38	4%
	Other	52	6%
Income	$< \$25,000$	188	22%
	\$25,000–\$49,999	184	22%
	\$50,000–\$74,999	185	22%
	\$75,000–\$99,999	110	13%
	\$100,000–\$124,999	81	10%
	\$125,000–\$149,999	61	7%
	$> \$150,000$	27	3%
Health	Disability	146	17%
	Chronic	238	28%
Age	Under two years	37	4%
	Between 2–10	105	13%
	Between 11–17	120	14%
	Between 18–64	575	69%
	65+	257	31%

Total households = 837.

https://doi.org/10.1371/journal.pone.0234381.t003

Given that the p-value is less than 0.05, results from the Fisher z-tests to infrastructure disruptions compared to their reference group. However, not all of the differences were proven to be statistically significant. Table 4 presents sociodemographic groups that experienced statistically significant disparity in well-being impact due to infrastructure disruption. It includes the dimension of well- being and the infrastructure service in which disparity was prevalent, the Spearman correlation coefficient of the association for the sociodemographic group and reference group, as well as the z-score resulting from the Fisher z-score coefficient difference tests. All coefficient values represented in this table are significant at p > 0.01.

Table 4: Subgroup populations experiencing disparity by well-being dimension and infrastructure service

Subgroup	Well-being Dimension	Infrastructure Service	Rho	Reference Group Rho	Fisher z-score
Black/African American	Upset	Transportation	0.502***	0.323***	2.28
	Helplessness	Solid Waste	0.451***	0.293***	1.93*
	Depression	Food	0.513***	0.224***	3.56*
	Anxiety	Food	0.425***	0.248***	2.12*
	Upset	Food	0.420***	0.212***	2.45*
	Safety	Food	0.470***	0.232***	2.86*
	Helplessness	Food	0.502***	0.236***	3.27*
	Daily tasks	Solid Waste	0.420***	0.241***	2.07*
	Daily tasks	Food	0.500***	0.224***	3.38*
	Distance	Food	0.460***	0.285***	2.09*
Asian	Anxiety	Food	- 0.352*	0.285***	3.23*
	Safety	Water	- 0.243	0.319***	3.18*
Other	Safety	Solid Waste	0.645***	0.351***	2.57*
	Anxiety	Solid waste	0.597***	0.319***	2.31*
	Daily Tasks	Solid Waste	0.612***	0.241***	3.00*
	Upset	Solid	0.528***	0.312***	1.70*
	Depression	Solid	0.579***	0.308***	2.20*
	Distance	Solid	0.573***	0.338***	1.93*
	Helplessness	Solid	0.563***	0.293***	2.16*
Low-income	Distance	Transportation	0.398***	0.243***	2.00*
	Daily tasks	Solid Waste	0.328***	0.158**	2.09*
	Distance	Solid Waste	0.369***	0.198***	2.16*
Middle Income	Daily tasks	Solid Waste	0.348***	0.158**	2.35*
	Distance	Solid Waste	0.454***	0.198***	3.32**
Children (11–17 years)	Safety	Water	0.445***	0.281**	1.87*
No Health	Distance	Communications	0.344	-	2.11*
	Daily Tasks	Communications	0.349	-	2.07*
Chronic Health	Depression	Solid Waste	0.425***	0.270**	2.30*
Disability	Distance	Water	0.489***	0.330***	1.97*
	Distance	Food	0.462	0.285***	2.12*

https://doi.org/10.1371/journal.pone.0234381.t004

Based on the rho values alone, well-being dimensions measured by the *"Ability to do daily life tasks"* and "*Feeling distant or cut off*" appear to be more strongly associated with well-being impact as compared to the other dimensions considered in this study. *"Feeling depressed"* or *"feeling upset"* did not have as significant or influential associations with infrastructure disruptions. The association between well-being and infrastructure disruptions was disproportionately stronger for Black and African American households compared to both the reference group (White) and other racial groups. On the other hand, infrastructure service disruptions did not have a significant impact on the well-being of Asian households, for which most rho coefficients were below 0.20 and or negative. For example, a negative correlation between disruptions in Food services and "*feeling anxious*" was found (rho = -0.352, p<0.01). The association between "*difficulty doing daily tasks*" and disruptions in electricity services is the only significant positive rho coefficient found in Asian households (0.336, p<0.01).

In the remainder of this section, findings specific to each subgroup population, followed by infrastructure service are presented in detail.

Well-being Impact Disparities Among Subpopulations

Race and ethnicity

Table 5 highlights the strongest associated well-being dimensions and service disruptions contributing found for each ethnic group. In general, for all racial and ethnic groups, changes in well-being appear to be most associated with most disruptions in food access, followed by transportation, and solid waste services. Only households identifying as *Black* and *Other* were associated with disproportionately greater well-being impact due to ser- vice interruptions, with respect to the reference population. For Black households, the results indicate moderately high correlations between all well-being components and disruptions in Transportation services followed by Food (0.40<rho<*0.51*, p = 0.001). Although weaker with respect to other infrastructure services, Communication service disruptions appear to have had disproportionately impacted the well-being of African American households (rho =, reference rho =). Households identifying as *Other*, interestingly, showed significant correlations between disruptions in Solid Waste services and all well-being dimensions, most notably Safety (rho = 0.644).

Table 5: Characterization of racial and ethnic groups by the strongest associated well-being and infrastructure disruption

Race/Ethnicity	Well-being Dimension	Infrastructure Service
Black	Depression, Daily-tasks	Food, Transportation
White	Anxiety	Transportation
Asian	Daily-tasks	Electricity
Latino	Daily-tasks	Communications
Other	Safety	Solid Waste

https://doi.org/10.1371/journal.pone.0234381.t005

Conversely, correlation analysis conducted for Asian households suggests minimal well-being impact due to disruptions in infrastructure, indicated by both negative correlations and insignificant coefficients at p<0.05. It is interesting to note, however, the association between Electricity and Daily tasks (0.33627), was the only non-negative coefficient higher than 0.30 at p<0.05. The correlation between disruption and well-being impact for the reference group population was moderately low, where coefficients of all well-being-disruption relationships were below 0.40, p = 0.001. The strongest association for White households was found between Anxiety and disruptions in Transportation services (0.3844195, p = 0.001). Latino households, similar to White households, had moderately low correlations. However, while the difference was not found to be statistically significant from the reference group, the association between communication disruptions and "*difficulty with daily tasks"* as well as solid waste disruptions and *"feeling distant"* are notable for Latin households.

Income

Table 6 shows the strongest associated well-being dimensions and service disruptions contributing to the well-being impact for each income group. In general, the correlation between well-being impact and infrastructure disruptions for low-income households was stronger compared to middle and high-income groups. High-income households are characterized by low to mild correlations where disruptions in transportation and association with the dimensions, "*feeling upset"* (0.3971156, p<0.001) and *"feeling anxious"* (0.389103, p<0.001) were the highest rho values. As for low-income households, the associations between all well-being dimensions and transportation disruptions were comparably stronger. All well-being dimensions for low-income households fell between 0.399 and 0.43 p<0.001, where the dimensions "*difficulty with daily tasks"* (0.4314670, p<0.001), and *"feeling anxious"* (0.4373609, p<0.001) were the highest rho values. For Middle-income households, solid waste disruptions appeared to have the most significant impact on well-being ("*feeling distant*," 0.4539269, p<0.001)

Table 6: Characterization of Income groups by the strongest associated well-being and infrastructure service

Income Level	Well-being Dimension	Infrastructure Service
Low	Daily-tasks, Anxiety	Transportation
Middle	Distance	Solid Waste
High	Upset	Transportation

https://doi.org/10.1371/journal.pone.0234381.t006

Age

Table 7 shows the strongest associated well-being dimensions and service disruptions contributing to the well-being impact for each Age group. Households without any children or elderly residents were more likely to experience well-being impacts due to disruptions in transportation and solid waste, whereas "*feeling distant*" was the strongest associated well-being. Weak correlations between well-being and infrastructure disruptions were observed within the Elderly subgroup population. Households reporting at least one or more Elderly resident have a stronger positive relationship between "*feeling helplessness"* and all infrastructure disruption categories (rho < 0.30, p<0.001). However, no coefficient exceeds 0.40 concerning all disruption and well-being categories. Based on the results, it is apparent that infrastructure disruptions alone did not contribute to significant impacts on the well-being of households with elderly residents. However, higher rho values tend to be associated with transportation disruptions. *"Safety"* and "*difficulty with daily tasks"* characterized the infrastructure disruption experience of households with children between the age of 11 and 17.

Table 7: Characterization of Age groups by the strongest associated well-being and infrastructure service

Age Group	Well-being Dimension	Infrastructure Service
Under 10	Distance, Safety	Solid Waste
11–17	Safety; Daily-tasks	Water, Communications
18–64	Distance	Solid Waste
Over 65	Helplessness	Transportation

https://doi.org/10.1371/journal.pone.0234381.t007

Interestingly, it does not appear that one infrastructure service dominates over another, in terms of its ability to impact household well-being. The strongest associations occur between disruptions in water infrastructure and the well-being dimension, *safety"*, in addition to disruptions in communications and *"difficulty with daily tasks."* Households with children under ten years follow a similar trend in well-being impact; however solid waste disruptions appear to have a wider-spread impact: all measures with well-being have coefficients greater than 0.35 ($p<0.001$). The most significant relationships among households with children under ten were found between solid waste disruptions and "*feeling distant"* (0.4653714, $p<0.001$), followed by solid waste disruptions and "*safety"* (0.4558314, ($p<0.001$).

Health

Table 8 shows the strongest associated well-being dimensions and service disruptions contributing to the well-being impact for each Health group. For households with disabled residents, well-being is correlated most with feeling distant; moderate coefficients were determined for water, food, solid waste, and transportation disruptions (in order from strongest to weakest coefficients). Furthermore, disruptions in solid waste services appeared to have a broader impact on reported well-being: *feeling distant, unsafe, anxiety, and difficulty doing daily tasks* were all moderately correlated with solid waste service disruptions. Households without reported health conditions experienced stronger impacts with respect to certain well-being dimensions than those with Chronic illness or Disability, as shown in Table 5.

Table 8: Characterization of Health groups by the strongest associated well-being and infrastructure service

Health Group	Well-being Dimension	Infrastructure Service
Chronic Illness	Distance, Safety	Solid Waste
Disability	Distance	Water, Food
No pre-existing health condition	Upset, Anxiety, Daily Tasks	Transportation, Electricity

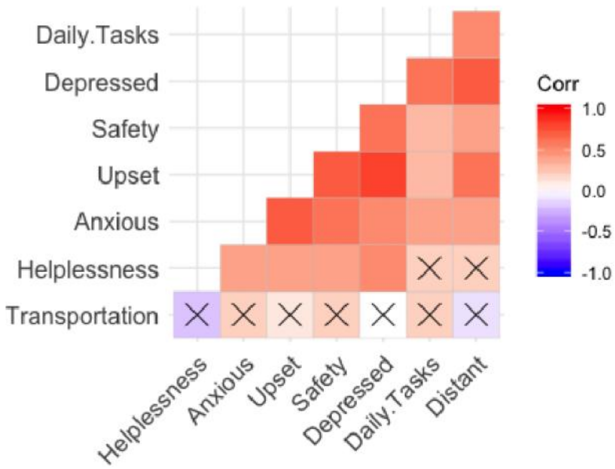
https://doi.org/10.1371/journal.pone.0234381.t008

Households with disabled occupants had more frequent and moderate associations with feeling distant with respect to disruptions in water (0.4892208, $p<0.001$) and food infrastructure (0.4617829, $p<0.001$). The broad well-being impacts of solid waste disruptions are also found from the correlation analysis for disabled households, indicated by the frequency of rho values higher than 0.35. Households with chronic health conditions followed similar trends to those of disability, but values were milder. Overall, coefficients for households reporting disability were stronger compared to households with no reported health conditions or chronic-health households.

The Influence of Different Infrastructure Disruptions on Well-being Dimensions

Transportation

Of the 15 subgroups (including the reference groups for each domain), 14 groups apart from households identifying as Asian, the rho coefficients measuring the relationship between *feeling anxious* and disruption in transportation were greater than or equal to .35. Six subgroups contained a rho value of .40 or higher (Low income, Black, Hispanic, or Latino, Under ten years old, Chronic Health, No Health Condition). Despite the common theme of *anxiousness* with respect to transportation disruptions, the strongest associations occurred within the analysis of Black households, where the strongest correlation occurred with the dimensions *feeling upset*(0.50233, $p<0.001$), followed by *feeling anxious* (0.4549, $p<0.001$). Both are statistically different from the reference group, signifying a significant disparity in the well-being impact due to disruptions in transportation, influenced by racial and ethnic minority status. Other dimensions of well-being that were impacted by disruptions in transportation services include: *feeling distant*, *difficulty carrying out daily tasks*, and *feeling helpless*. The least impacted households by transportation services were households identifying as Asian (Fig 8), Disabled, over 65, and *Other* race.



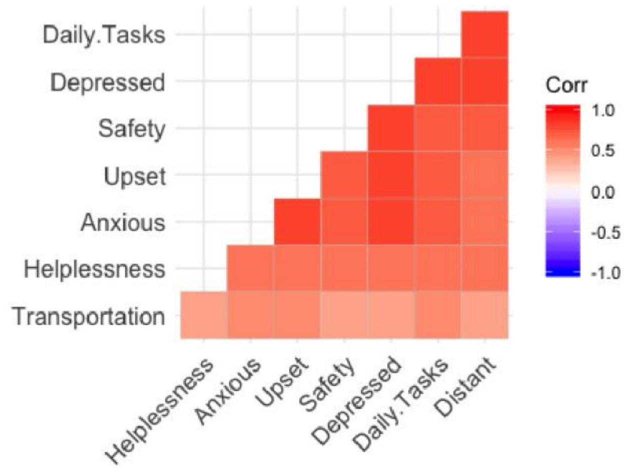


Figure 8: Well-being and transportation disruption experience correlation matrix for Asian Households (Left), Black and African American households (Right).

Solid waste

Similar to transportation services, solid waste disruptions appear to have a negative impact on the well-being of all subgroup populations, in which *feeling distant*, *safety*, and *daily tasks* resulted in the strongest rho. The highest rho value was the result of the correlation with *safety* (0.65 $p<0.001$) followed by *daily tasks* (0.61, $p<0.001$), with respect to households identifying as "Other" race or ethnicity. The difference from the reference group is statistically significant, indicating a racial disparity in well-being risks due to disruptions in solid waste services.

Electricity

Less than half of the subgroup categories were associated with the same well-being dimension, so we are unable to categorize electricity disruptions with a single or particular cluster of well-being dimensions. The strongest rho value is the measure between electricity disruption experience and *daily tasks* for Black or African American households (0.4335 $p<0.001$). Interesting to note are the negative correlations reported by Other and Asian groups.

Food

We observe a similar trend for Food services: less than half of the subgroup categories were associated with the same well-being dimension, so it is not possible to categorize electricity disruptions with a single or particular cluster of well-being dimensions. The disruptions in food services were most strongly correlated to ‘feeling depressed' in *Black or African American* households (rho = 0.51287, $p<0.001$), followed by helplessness and daily tasks (0.5018 and 0.5003, both at $p<0.001$).

Water

Interruptions in water services is associated more strongly by ‘feeling helpless’, for eight subgroups (Low income, High income, Black, Hispanic or Latino, 11–17 years, between 18–64, No health condition, Disability), followed by ‘difficulty doing daily tasks’ (Low income, middle income, Black, under 10 years, 11–17, No health condition, Disability). The strongest relationship, however, is between households with disabled members and ‘feeling distant’ (rho = 0.48, $p <0.001$).

Communications

Less than half of the subgroup categories were associated with the same well-being dimension; therefore, we are unable to characterize communication disruptions with a single or particular cluster of well-being dimensions. We see a moderate correlation between the difficulty of doing daily tasks, in which five groups (Low income, Black, Latino or Hispanic, 11–17 years old, and no existing health condition group), coefficients are greater than or equal to 0.35, $p<0.05$. Only a small number of the coefficients were above 0.35, signifying, in this case, that communication disruptions did not result in significant impacts on household well-being during and following the disaster. Also, this may indicate that there was not an extensive disruption in communication services among the studied households. In the case of Hurricane Harvey, we can infer that communication infrastructure, in comparison to other infrastructure systems, was resilient against hurricane-related damages. Despite this, the disparity in experiences was still found: Black households (0.46, $p<0.001$) and Latino households (0.4, $p<0.001$) were more strongly associated with communication disruptions compared to both the reference group and other ethnic groups, similarly, age group 11–17 (0.43 $p<0.001$).

DISCUSSION

This effort is among the first studies to systemically and empirically evaluate the social inequalities related to well-being risks in the context of infrastructure resilience. The results of this study provide empirical grounding and evidence of the inequitable state of risks due to infrastructure disruptions. In the context of this study area and Harris County in Harvey, disruptions in *transportation*, *solid waste*, *food, and water* infrastructure services resulted in more significant well-being impact disparities as compared to *electricity and communication services*. It is likely that the planning and preparation efforts taken by communication service companies led to limited disruption and rapid restoration that buffered the impact of disruptions on households during the storm. In fact, only 5% of the wireless networks in Harris County experienced outages [92], where 283,000 households lost wired phone services at the peak of the outage in contrast to more than 3 million phone lines in Hurricane Katrina and one quarter of wireless networks in Superstorm Sandy (FCC, 2017). The utilities prepared by topping off all generators ahead of the storm and purchasing spare fuel and having refueling trucks on standby at specific locations (Bubenik, 2017). In case of damages to fiber lines, microwave technology was used to temporarily bridge gaps where fiber lines were disconnected from cell towers to communication centers. Power outages during Harvey never exceeded 350,000 customers at any time, compared to millions that lost power in Hurricane Ike and Hurricane Katrina (Walker, 2017).

Furthermore, the average reported days of electricity disruptions in the sample households is 0.790 days, while the average duration of wireless and internet service outages were 1.18 and 0.845 days, respectively. This is in contrast to the average five days of household reported duration in transportation service interruptions. This can be an example of how strategic resilience planning, as well as retrofit and mitigation investments for disaster, can improve the resiliency of infrastructure systems and minimize the impact on households during a disaster, contributing to the household and community resiliency.

Based on the analysis, factors such as their ethnicity and household income affect the amount of tolerability that a household can emotionally and mentally withhold when experience hardships due to service disruptions. Using the correlation analysis, this study discovered disparities in well-being experience due to disruptions in infrastructure services, primarily with respect to racial or ethnic groups. In particular, the results showed the strongest correlations between their well-being and infrastructure disruptions, namely Food and Transportation, for households identifying as Black or African American. Households identifying as *Other* ethnicities, which comprised of Native American, Pacific Islander, and Multiracial families experienced significant disparity in well-being experience concerning Solid Waste services. While not statistically significant according to the fisher z-testing analysis, the results for other minority groups and vulnerable group populations had overall stronger associations between well-being impact and disruptions compared to the reference group (non-vulnerable) population. These findings suggest that the risks of infrastructure service disruptions disproportionately affect the well-being of vulnerable populations. The remaining of the discussion is organized concerning the research questions guiding the analysis.

The Association Between Disruptions and Well-being Dimensions

Fig 9 is a visual representation of the well-being characterizations of the six critical infrastructure systems examined in this study. Different sub-group populations experience different levels of well-being risks due to disruption in infrastructure services. For example, the correlation analysis shows that households identifying as Black and African American experienced greater well-being impact compared to other sub-group populations. Also, well-being impacts found in households identifying as Black and African American had stronger associations with disruptions in food, transportation, and solid waste services. Secondly, different components of well-being were found to be associated more strongly with certain infrastructure services. In general, service disruptions were more likely to results in households feeling helpless, having difficulty doing daily tasks, and feeling distance from their community. In some subpopulation groups, feeling more distance or disconnected from their community was significantly correlated with disruptions in solid waste services. A systems analysis would be needed to investigate the influencing factors of such relationships.

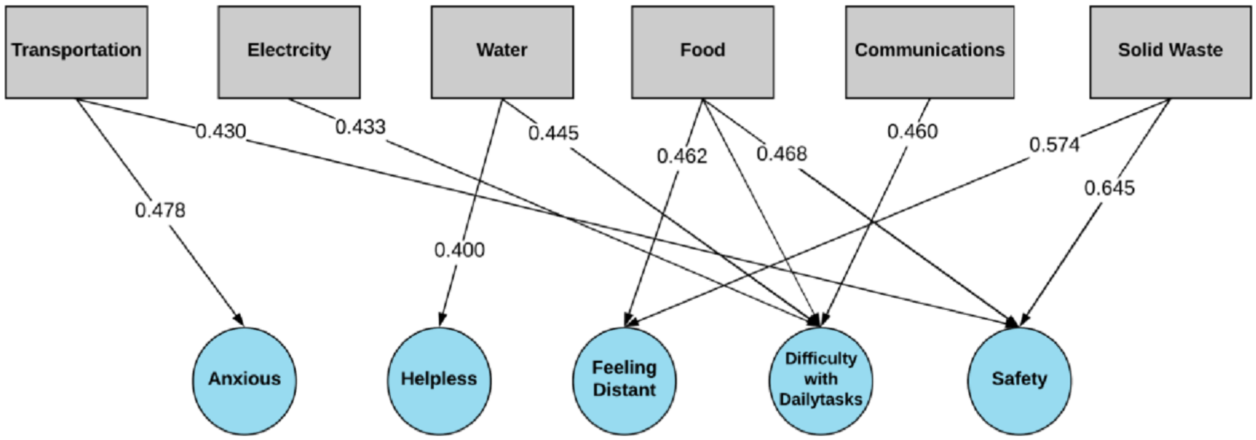


Figure 9: Service disruption characterization. The characterization of service disruptions by average Spearman's rho and most frequently associated well-being dimension according to all subgroup populations is shown. Service disruptions are frequently associated

The moderate levels of correlation coefficients hint towards additional factors that influence well-being changes as a result of infrastructure disruptions during disasters. Those factors influencing well-being risk disparities include variations in the level of preparedness, perceived risk of disruptions, and ability to adjust to disruptions. The influence of these factors is not considered in the current analysis and will be the next step for this research.

The results from the correlation analysis confirm that infrastructure disruption impact on communities is indeed heterogeneous. In the context of Hurricane Harvey, vulnerable groups have a higher sensitivity to service disruptions. Using Fisher z-score tests, significant disparities in well-being experience were identified across racial or ethnicity, income level, health status, and age group (Table 5). However, the race and ethnicity of households appear to hold more considerable influence on disparities in well-being, compared to other factors surveyed in this study, such as income, age, and health

The insignificance in the correlation between well-being impact and infrastructure hardship experience for Asian households and the more significant correlations for Black households is very telling and indicative of the inequalities that exist in infrastructure service disruption impacts. The minimal disparities and difference in well-being impact across the age group categories confirm what many researchers in behavioral science and psychology have already found, but specific to the context of infrastructure disruptions. Outside the context of infrastructure disruptions, some studies theorize that the relationship between age and well-being is a relatively stable one, with a tendency to increase slightly with age (Keyes & Beyes, 2003). Others argue that well-being is not actually influenced by chronological age (Myers & Diener, 1995) and that other factors such as physical health status and conditions of living are more significant in determining the well-being of people (Horley & Lavery, 1995). Similarly, Khumalo et al. (2012) found that older adults are more likely to have higher mental well-being than those younger than them. While the findings from these studies are not specific to disasters or infrastructure system disruptions, they help to shed light on the outcomes of this analysis. In the case of this study, households with elderly residents were less susceptible to well-being impact due to Electricity and Communication Services, and for the other infrastructure services, elderly households often fared better compared to their reference group. For households with elderly occupants, disruptions in infrastructure services did not appear to have strong correlations to changes in well-being.

More significant variation and disparity in well-being impact among households grouped by income level were anticipated. However, the results rejected the presence of well-being impact disparities for households with different income levels. Mirroring the findings of Stewart-Brown et al. (2015) on subjective well-being and income in a general context, well-being associations were relatively constant among all income groups apart from the categories displayed in Table 5. Their study found no evidence of a dose-response relationship for income and high mental well-being. In general, the chance of low mental well-being was increased along with reduced income, but those in the second lowest income bracket were more likely to have low mental well-being than those in the highest (although those in the lowest income bracket showed no difference to the highest). While those in the highest income bracket were more likely to have high mental well-being than those in lower brackets, the four lowest brackets showed very similar levels of high mental well-being. This finding also points out the role of other influencing factors such as preparedness, previous experiences, and risk perception.

Well-being Disparities Among Subpopulation Groups

Certain infrastructure services cater more towards specific demographics, mainly communication services. The well-being of Households with older children (11–17) or no children was correlated more strongly to disruptions in communication services, in comparison to the Elderly and households with children under the age of 10 years. Research has shown that older adults are slower in adopting new technologies than younger adults (Czaja et al., 2006). Older adults (60–91 years) were less likely than younger adults to use computers and the internet (Vaportzis et al., 2017). Likewise, younger children under the age of 10 years are less likely to use communication services directly. Young adults and adults may have a higher dependency on communication services due to education needs and work-related purposes. Changes to communication service can thus harm their well-being state, more so than other age groups as the correlation analysis suggests.

Just as particular infrastructure services have more significance to different population groups, certain well-being dimensions are more associated with different infrastructure services. This information provides more insight into which infrastructure systems were more resilient in terms of population impact. In the context of Hurricane Harvey, Electricity, Communications, and Food services were weakly correlated to well-being impact for most population groups, apart from African American households. This might be an indication that these systems were not severely disrupted. There is also a tendency of well-being impacts due to infrastructure service disruptions to be more related to social needs of households, as opposed to emotional needs. This distinction reinforces the idea that infrastructure systems support the social fabric and connectivity of communities.

Resilient infrastructures and resilient communities go hand in hand. Some well-being dimensions are more impacted than others due to different infrastructure service disruption's impact. This is an important observation because it indicates the ways through which infrastructure service disruptions impact humans. *'Feeling distant or cut-off'* and '*feeling difficulty in doing daily tasks'* means that disruptions in services interrupt the household's ability to feel like productive members of their community. Being distant from the community and unable to make contributions lead to communities being more disconnected, and as a result, less resilient in the face of calamities and disruptions. While the relationships in this study are associative rather than causative, the findings show disparities in well-being impacts of infrastructure disruptions for different vulnerable sub-populations.

FUTURE WORK

The primary focus of this study is to empirically examine the relationship between infrastructure disruptions and households' well-being, which is an understudied area in the field of infrastructure resilience. It is out of the scope of our paper to assess why certain infrastructure systems cause more impact in certain well-being dimensions than others. Future studies can examine the underlying mechanisms that influence the well-being impact disparities identified in this study due to various infrastructure service disruptions.

While the study was able to show an empirical relationship between well-being impact and certain sociodemographic characteristics of households and that there is a disparity that is related to sociodemographic characteristics, the study does not look into the specific factors that influence this apparent disparity. Further analysis would focus on narrowing in on the latent influencing factors that predispose vulnerable populations to greater well-being impact compared to other households. The future studies of the authors will investigate the association of other social factors such as gender, as well as characteristics particular to disaster situations such as preparedness, previous experience, expectations, and social capital on the well-being impacts of infrastructure disruptions.

Furthermore, this study does not analyze the combined effects of infrastructure disruptions on household wellbeing. For example, disruptions in transportation services and road access may have influenced African American households' access to food services at more significant levels compared to other services and non-African American households. Similarly, certain significant associations between particular well-being dimensions and infrastructure service disruptions, such as 'feeling distant' and solid waste service disruptions, need to be investigated further to uncover why certain disruptions impact particular well-being dimension more than others. Looking at the combined effects of infrastructure systems from a systems-of-systems perspective would help community planners pinpoint fundamental infrastructure interactions that contribute to higher impact in vulnerability in certain population groups.

CONCLUDING REMARKS

This paper addressed critical gaps in empirical knowledge surrounding household-infrastructure disruption interactions. The purpose of this paper was to advance the understanding of household-infrastructure system dynamics and break new ground in our understanding of social inequality of the risk impacts due to service disruption. The empirical analysis presented in this study confirms that there are household level influencing factors that are associated with the differential impact of service disruptions on households during a disaster event. Disparities in well-being impact were most prevalent among racial minority groups related to disruptions in transportation, solid waste, and food services.

Furthermore, the inclusion of well-being as a measure of the household level impact allowed us to determine which aspects of well-being infrastructure disruptions are more strongly associated. Infrastructure disruptions associated with the greatest disparity also tended to have strong correlations to multiple well-being dimensions. Similarly, subgroups experiencing impact disparity, such as Black and Other households, tend to have high associations with multiple well-being dimensions.

To the best of authors' knowledge, no prior studies have been attempted to systematically assess the impact of multiple infrastructure disruptions and well-being dimensions. As a result, multiple novel perspectives and understanding of household-infrastructure disruption dynamics were uncovered through this study to enable an equitable resilience approach in infrastructure systems.

The results from this research have interdisciplinary applications and implications by encouraging the integration of social dimensions into disaster planning and prioritization of infrastructure systems. As a result, the inequity in impacts that sub-groups experience when different infrastructure services are disrupted can be examined more effectively, and the extent to which infrastructure service disruptions create disproportionate risks for different sub-populations can be understood.

ACKNOWLEDGMENTS

The authors would like to acknowledge the support of researchers in the social sciences from the TAMU Public Policy Research Institute (PPRI), as well as Dr. Philip Berke of the Department of Landscape Architecture and Urban Planning in the design of this study's survey and analysis.

CHAPTER III: STUDY 2 - VULNERABLE POPULATIONS AND SOCIAL MEDIA USE IN DISASTERS: UNCOVERING THE DIGITAL DIVIDE IN THREE MAJOR U.S. HURRICANES [‡]

OVERVIEW

How populations use social media in disasters is essential for evaluating the representation of subpopulations while analyzing social media data for emergency response and disaster research. Existing machine learning models can extract, characterize, and make sense of digital trace data from social media, but are unable to account for diversity in population groups and use of social media. Consequently, the reliability of their decision-making ability remains questionable. This paper presents an exploratory analysis of empirical household survey data on the information seeking, sharing activity, and perceptions of information reliability on social media platforms across different population groups during three major hurricane storm events in the United States between 2017 and 2018. The results of this analysis suggest significant associations between social media use and socioeconomic factors: (1) Socioeconomic factors along with geographic effects play a role in determining not only platform uptake but both motivations for information seeking and the action of information sharing on social media, (2) The type of social media platform influences the type of information people seek, (3) Households from lower socioeconomic and minority backgrounds were more likely to use social media platforms to seek out different

[‡] Published as a journal article in the *International Journal of Disaster Risk Reduction* as Dargin, JS, Fan, C, Mostafavi, A.(2021). Vulnerable populations and social media use in disasters: Uncovering the digital divide in three major U.S. hurricanes, International Journal of Disaster Risk Reduction Volume 54,https://doi.org/10.1016/j.ijdrr.2021.102043.

information on social media than their peer, (4) perceptions of information reliability are also influenced by social divides, where households in rural areas, lower income groups, and racial minorities were more likely to report greater unreliability in social media information. These findings provide new insights into the roles of social media use in creating or dismantling the digital divide during disasters.

INTRODUCTION

During Hurricane Harvey, first responders witnessed unusual activity on social media by individuals seeking assistance due to overloaded 911 calling systems (Seetharaman & Wells, 2017). In addition to contacting for emergencies, the general public turned to social media for situation awareness (information checking) (de Albuqueruque et al., 2015; Yu et al., 2019), information sharing (Becker et al., 2017), rescue coordination, and volunteer efforts. According to the Structural Influence Model of Communication (SIM) (Viswanath, 2006) applied in health disparity research, any differences among social and racial-ethnic groups in the use of communication channels, such as social media platforms, could result in both an indirect and direct effect on risk exposure and impact in the context of health outcomes. As a result, existing disparities among vulnerable groups can be exacerbated due to differences in social media access and use (Vaughan & Tinker, 2009; Viswanath & Kreuter, 2007;Viswanath, 2006). In disaster situations, it is not likely to be very different as “the fundamental issues of inequality and stratification at the heart of sociology are usually at the margins of communication studies” (Earl, 2015).

While social media platforms (Facebook, Twitter, Nextdoor) have become powerful tools used by the public to cope with disasters, researchers in the field are becoming acutely aware of the potential population biases and misrepresentations (Mendoza et al., 2010) inherent to digital trace data from social media platforms. Machine learning techniques have been applied to classify and characterize data from social media in the context of disasters and analyzing the nature of information dispersion and networks during disasters (Gao et al., 2011; Guan & Chen, 2014; Nagar et al., 2012; Rester et al., 2019; Xiao et al., 2015; Chao et al., 2020; Zhang et al., 2019). Some research has used social media data (such as tweets) to determine social media usage disparities. Their conclusions suggest that because certain population groups are not active on social media during disasters, based on their metrics, they are at greater risk due to communication gaps (Samuels & Taylor, 2019; Wang et al., 2019).

Differences in population representation across social media platforms are well-documented in research conducted over the last decade from gender representation (Viswanath, 2006) and across factors such as race, ethnicity, and parental educational background (Hargittai, 2007). Several studies have recognized the presence of population bias in digital trace data from Twitter and its problematic implications (Jiang et al., 2019; Malik et al., 2015; Mislove et al., 2011). Social and demographic factors have been found to influence preferences for social media platforms (Jiang et al., 2019; Mislove et al., 2011; Ottoni et al., 2013); as well as the use of platform mechanisms (Olteaunu et al., 2019). However, a significant pitfall of machine learning algorithms for social media data is that they tend to assume uniform usages of social media across population groups and accurate representations of the target population. Making such assumptions not only misrepresents certain groups of users but also influences the performance of various prediction models (Cohen & Ruths, 2013). Therefore, research outcomes are at risk of informing discriminatory decisions (Olteanu et al., 2019), which is in complete contradiction to an overarching goal to achieve social equity and remove barriers and disparity in disaster recovery and resiliency of communities.

Similarly, the digital divide due to uneven access to social media platforms and different motivations for social media use can distort the situational awareness created during disasters (Xiao et al., 2015) and lead to significantly underestimated needs of the population and compromise the external validity of research and performance of algorithms that make inferences about social media data (Olteanu et al., 2019). There are further concerns over the reliability of the information derived from social media sources (Goodchild & Glennon, 2010; Goodchild & Li, 2012). As a result, decisions made based on models and studies using data with skewed population representation can result in unintended outcomes such as disparities in the emergency response and protection of disaster victims in a given area (Vaughan & Tinker, 2009).

To date, few empirical studies exist which rigorously document the digital divide in social media and the user experience during situations like a disaster (Chou et al., 2009; Jones & Fox, 2009). Conversely, research has been geared more towards the needs of emergency response workers (Reuter et al., 2019; Hiltz et al., 2020) and organizations in terms of using social media data to make decisions and less on the users that are creating content and developing tools to manage social media data and how software can better support the social media needs of emergency managers (Reuter et al., 2019). Eismann et al. (2016) conducted a systematic literature review on collective behavior in social media in disaster situations, finding that disaster characteristics do, in fact, collective influence behavior in social media in response to the respective disasters.

RESEARCH SCOPE

More robust methodological investigations about the nature of population representation in social media are needed to produce an empirical understanding of digital divide issues (Ruths & Pfeffer, 2014; Tukekci, 2014) related to experiences during disasters. This paper builds upon existing research of social media bias and inequality by examining the social and geographic factors influencing the digital divide in different areas impacted by a crisis. Cross-sectional data on the use of social media platforms (Facebook, Twitter, Nextdoor) by different population groups in the aftermath of three major U.S. hurricanes occurring between 2017 and 2018 (Harvey, Florence, and Michael) was collected through three separate household surveys. Using descriptive statistics, ANOVA testing, and fitting regression models, an analysis of social media uptake, social media platform use, social media behaviors and purpose of use, and information reliability across social groups and locations impacted is presented.

The research will unfold the underlying social and geographic determinants for using social media platforms during disasters. Understanding the usage of social media used by households to gather and share information helps identify population needs and target platforms. In terms of addressing social media data biases, the results may address findings from studies using social media data that find the underrepresentation of minority groups and support empirical evidence for social media data biases. Findings from this paper will provide valuable insights into the geographic disparities of social media use during disasters. They will expand knowledge on the roles of social media use in creating or dismantling social and geographical disparities during disasters. The outcomes of this research also intend to inform advanced methods of data mining of social media data to produce useful and valid scientific information and minimizing biases. The current analysis could confirm whether the reported results based on social media data are valid.

The analysis focused on identifying the determinants of social media use and behaviors across different population segments and contexts and how social media platforms influence information-seeking behaviors among users.

More specifically, our guiding research questions are:

(1) To what extent do information sharing and seeking behaviors differ across different social groups and geographic locations?

(2) How does the perception of social media information vary by different social factors and platforms?

(3) To what extent is the social media platform associated with the information people seek during disasters?

(4) To what extent social media use vary across different disaster-afflicted regions (i.e., Harvey vs. Michael vs. Florence) and urban versus rural settings?

The following section will discuss the latest findings in social media usages during disasters, documented disparities in digital uptake and its repercussions in the communication of information at a general level, and information sharing and checking actions and reliability of the information on social media.

BACKGROUND

Disaster Communication and Social Media

Communication is central to facilitating community resilience during disasters (Houston et al., 2015; Nicholls, 2012; Pfefferbaum & Klomp, 2013). A disaster can be traced back to a crisis in the communication process or the result of a communication breakdown (Rodriguez et al., 2007; p. 479). Mass mediated disaster communication generally consists of disaster warning messages and mass media news coverage of disasters disseminated through official government organizations on the radio or television. (Rodriguez et al., 2007; p. 482) contend that mass media coverage of disasters has a significant influence on how people and governmental organizations perceive and respond to disaster events (Rodriguez et al., 2007; p. 479). Hence, disaster communication has the power to influence individual disaster knowledge, attitudes, and behavior, which control one's “situation awareness.” Situation awareness is defined as “all knowledge that is accessible and can be integrated into a coherent picture, when required, to assess and cope with a situation” (Sarter & Woods, 1991). During disasters, traditional media and other communication channels are often unavailable, lack timely response, and insufficient given the urgent needs of those seeking information (Chen et al., 2014). At the same time, mass-mediated coverage of disasters through traditional channels is limited in that it usually involves messages created by a single source and disseminated to large audiences, with little opportunity for audience response and participation.

Web-based social media has become an influential platform for disaster communication and has been considered advantageous over traditional media outlets (Houston et al., 2015). Compared to traditional media, web-based social media technologies have greater capacity, dependability, and interactivity, which would help enhance disaster communication. Social media also has advantages in information flow, information control, adaptability, relevance for residents, intelligence, empowerment, dependency on the power grid, cost, accessibility, and timeliness of information (Keim & Noji, 2011; p. 52). As a result, social media platforms have become critical spaces for situational awareness, or people to receive and share information about events unfolding (Palen & Liu, 2007). A key advantage the platforms offer is delivering real-time emergency information to the affected people on time (Kim et al., 2018). Having timely access to factual information is crucial for actors to learn what is happening on the ground (Shaw et al., 2013; Vieweg et al., 2010). During earthquakes and floods, providing and receiving information about disaster response activities and opportunities using social media is highly cited as recognized by Carter et al. (2018). Social media has been used to communicate warnings (Carter et al., 2018; Ahmed & Sargent, 2014; Chatfield et al., 2013; Hughes et al., 2014) and preparedness information (Chatfield et al., 2013; Ahmed & Sinnappan, 2013), raise awareness of the disaster and promote fundraising (Ahmed & Sinnappan, 2013; Smith et al., 2015; Takahashi et al., 2015), and seek and provide emotional support (Ahmed & Sinnappan, 2013). Houston et al. (2015) introduced a disaster social media framework of users and uses based on a comprehensive literature review. Their paper thoroughly discusses the various types of users (organizations, individuals, communities) active on social media during a disaster and the users' various uses of social media. It illustrates the variety of entities that employ and produce disaster social media content.

While advantageous for real-time situation monitoring, the “avalanche” of data is a common pain-point for emergency response and humanitarian relief organizations interested in using information derived from social media platforms (Castillo, 2016). Data from social networks is noisy: most social media posts do not include new or useful information and unverified, where many repeat information that is already available through other channels. Filtering through the mass amount of information is overwhelming (Bressler et al., 2012), and as a result, impractical for agencies to make use of for real applications (Cutter et al., 2016).

Social Media Platforms: Facebook, Twitter, Nextdoor

At present, various social media platforms are used in disaster-related communication, including popular platforms such as Facebook, Twitter, and Flickr (Briones et al., 2011; Palen & Liu, 2007), but also disaster-specific applications (Ludwig et al., 2015). Social media characteristics can help explain the structure and functions of interactions that take place on specific platforms (Kane et al., 2014). For example, Facebook and Twitter have different text limitations and features for posting information, which controls how users interact on the platform's space. Kane et al. (2014) identified four primary features of all social media platforms which help to distinguish them from one another: (1) The degree to which the platform allows unique “digital profiles” or user profiles, (2) The platform's “search and privacy” mechanisms which control how users access content on the platforms, (3) How users build and develop “relational ties”, (4) How the platform allows “network transparency.”

The different features made available by social media platforms can give way to different types of information or content or different perspectives of events happening during a disaster. This is an essential factor in assessing social media platform usage during disasters and determining platform divides, which may contribute to a disparity in information awareness and understanding of events. This study focuses on the use of Facebook, Twitter, and Nextdoor, which have been extensively used in recent disasters in the U.S.

Twitter

Twitter is the social media platform referred to most often in disaster and crisis informatics research (Zhang et al., 2019) and is often used to exchange disaster-related information by all social units in all disaster categories. It is beneficial for disaster relief professionals as it is easy to use and monitor, facilitates quick information dissemination, and can be updated anywhere [54]. Based on a review of literature, Twitter has been used for various protective action and disaster response efforts, including warnings (Ahmed & Sargent, 2014; Chatfield et al., 2013; Acar & Muraki, 2011), situational awareness updates (Ahmed & Sargent, 2014; Hughes et al., 2014; Smith et al. 2015; Cameron et al., 2012; Chatfield, 2012; Jung, 2012; Toriumi et al., 2011). Twitter is also used for functions that require two-way communication (Jung, 2012), such as inquiring about another's well-being (Acard & Muraki, 2011; Jung, 2012) and discussing events and their consequences (Jung, 2012; Gaspar et al., 2014; Kaufmann, 2015). An advantage of Twitter as a social media platform is its feature of sharing short messages and the ability to publish direct and indirect updates (Jung, 2012). Twitter has shown to be useful in reporting breaking news (Vis, 2013; Peters & Broersma, 2012), in some cases, faster than mainstream media outlets (Vosoughi et al., 2018).

Nextdoor

Nextdoor is a hyperlocal social media platform that connects its members based on geography, a unique relational tie, and network transparency feature not part of Facebook or Twitter's platform capabilities. Unlike Facebook or Twitter, the process for creating a Nextdoor account is less straightforward. Users must register using a verified address and are connected with nearby users based on geocoded addresses. In recent disasters (such as Hurricane Harvey), Nextdoor was used by residents to communicate and coordinate relief and rescue efforts in neighborhoods (Seethharaman & Wells, 2017). Recognizing how their platform can be a helpful tool during disaster situations, the official website of Nextdoor details how users of the platform can take advantage of the platform's features to get help and stay safe during hazardous situations. The above evidence shows that different social media platforms are being used in disasters. However, little is known about the extent to which different sub-populations use these social media platforms and how they use it. This understanding is essential for public officials and emergency managers to utilize social media during crises effectively and also for researchers to examine better data obtained from the different social media platforms (Nextdoor, 2020).

Facebook

Relative to Twitter, Nextdoor, and other existing social media platforms, Facebook is considered more "static" (Jung, 2012) and offers a broader audience base while enabling longer messages. In general, it is preferred for functions that require longer text messages and active communication. On this platform, the functions that prevail include relief coordination, keeping in touch with others, discussing events and consequences, and seeking advice (Chen et al., 2014). Bird et al. (2012) argue that Facebook (p. 32) "can be used to effectively and efficiently disseminate emergency information on the occurrence of hazards; location of evacuation centers and road closures; fundraising opportunities; volunteering; and reassuring people about the safety of family and friends." On Facebook, users can also express preferences and publish status updates. Facebook allows users to connect, facilitating establishing, and preserving relationships (Wilson et al., 2012) Facebook's Safety Check feature allows users to signal to those in their circle that they are safe or need help (Facebook, 2020).

The Digital Divide: Communication Gaps

Differences among social and racial-ethnic groups in the use of communication channels, such as social media platforms, could result in both an indirect and direct effect on risk exposure and impact in the context of health outcomes, according to the Structural Influence Model of Communication (SIM) (Viswanath & Kreuter, 2007). The model was tested in the context of health communication and health disparities, where it was found that health outcomes were positively correlated with communication inequalities [[64], [94]]. Another study confirmed the theory of the SIM: communication gaps between different social groups, including socioeconomic status, psychological perspectives, geographic factors, and social media use, were found to lead to unequal protection across society during an influenza pandemic (Vaughan & Tinker, 2009).

Therefore, it is proposed that existing disparities among vulnerable groups could be exacerbated due to differences in social media access and use (Viswanath & Kreuter, 2007; Vaughan & Tinker, 2009; Viswanath, 2006).

In disaster situations, the same social groups face similarly heightened risks and vulnerabilities. Given the role of social media platforms as tools for people to share and retrieve information during disaster events, it is imperative to assess the extent of the digital or social media divide among population groups concerning their use of and activity on social media platforms during disasters. Different social groups have different abilities to generate, disseminate, and use information and access, process, and act on it (Viswanath, 2006). Differences in population representation across social media platforms have been well-documented in research conducted over the last decade from gender representation (Ackerson & Viswanath, 2009) and race, ethnicity, and parental educational background (Hargittai, 2007; Muttarak & Lutz, 2014). Social factors have been found to influence social media platforms (Mislove et al., 2011) and use platform mechanisms differently (Olteanu et al., 2019).

Locational factors (urban vs. rural) have also been cited in the discussion of the "digital divide" and disaster resilience disparity. Looking at the difference in social media use patterns across urban and rural settings is important because the challenges in urban areas are different from those in rural places (Borden & Cutter, 2008). Rural areas typically lack sufficient human and financial resources compared to their urban counterparts, consequently comprising their resilience (Tootle, 2007). However, at the same time, and perhaps due to the limited resources available, rural places tend to become self-reliant and have stronger intra-community ties and social networks, enhancing resilience (Tootle, 2007). Finally, the impact of disasters is experienced differently in urban and rural settings: while property losses are more significant in urban areas because of the density and value of structures, the relative impact of those losses might be more significant in rural areas (Cutter et al., 2016). Fatalities and injuries might also be greater in urban areas for some hazards (e.g., heat, earthquakes) but not for others (lightning, flooding) (Borden & Cutter, 2008).

However, little is known about the determinants of social media access and use among different sub-populations and the extent to which inequalities exist for vulnerable populations in disaster situations. Based on the study of health outcomes disparities due to inequalities in health communication due to various social and geographic factors hints at possible severe disparities in disaster impact due to similar communication gaps resulting from different social media use habits and platform access. Having this context and understanding is vital because most models assume universal uses. If we have empirical information about the differences in social media use according to different contexts and population groups, we can develop more accurate models to lead to more impactful decisions.

Information Seeking or Checking

Information seeking or checking is a sense-making process where a person retrieves information that fits his or her point of view [68]. During disasters, people need information that will enable them to make sensible decisions and protective actions that ensure their well-being and safety. Bird et al. (2012) and Ryan (2013) explored motivators for social media use during disaster situations during flash flooding events in Australia. The most common reasons for use were to get information on the community's well-being and friends and family, share information, and offer assistance to others (Bird et al., 2012). People were further seeking information regarding various infrastructure service disruptions, including road closures and power outages, and work closures.

As noted earlier, social media platforms also have use for communicating information, online participation, social capital exchange, and visibility, all of which may be unevenly distributed among different social groups (Micheli, 2016). Education and income were the most significant factors for variation in Internet use among population groups (Witte & Mannon, 2010). Hargittai (2007) forewarned a 'second-level digital divide' concerning how people use web platforms from the types of activities they conduct, their digital skills, and the opportunities they can access (Micheli, 2016). These activities or behaviors are influenced by one's perception of information reliability and credibility, socioeconomic background (Micheli, 2016), social network, and trust (Borgatti & Rob, 2003). In other fields, literacy, and information-seeking behaviors play substantial roles in health outcome improvements (Tang et al., 2019). In their study, it was found that compared with the high-income population, low-income population groups were less likely to turn to healthcare professionals as their first source for health information, and overall, had more difficulty understanding the health information found. Individual, community, and content-level factors each influence a person's sharing and seeking activities. Variations in our social networks lead to different degrees of information salience and review and differences in information uptake and sharing (Southwell, 2013; Shumate, 2014).

Information Sharing and Perceived Reliability

Information sharing is an action to provide information to other community members who may need it (Gardoni et al., 2000; Park et al., 2014). The second-level digital divide discussed by Hagittai (2007) helps explain why certain population groups, based on socioeconomic status, are better-informed than others. Some are more socially connected, which influences the extent to which information is available and its quality. There are differences in how, when, and with what information is shared, which help maintain situation awareness inequalities (Constant et al., 1994;

Grand, 2014). It is proposed that the sharing and checking activities of subgroups of a population vary, reflecting their unique needs during a disaster. Disparities in the information-sharing matter, especially in the context of disasters. As presented by the social media platforms' descriptions, each platform has unique sharing options and ways that users can gather or seek information. In the distribution of information during a disaster, people need the information that will enable them to make sensible decisions about their and their families' well-being and safety.

A key aspect of information finding lies in the reliability of the information. The extent of reliability a person perceives information is dependent on several factors and is related to social factors (Li & Suh, 2015). These studies did not look into how information distributing behaviors might have differed concerning social contexts and the context of different disaster or hurricane characteristics. It is proposed that information sharing and seeking are unique to different population groups and indicate their specific needs. It would further highlight uniformity in machine learning models using social media data, which assume users have uniform uses.

It is proposed that the unique features of social media platforms provide different information sharing and checking capabilities that might influence the extent of an individual's sense-making process. As a component of this analysis, information checking purposes will be assessed and compared across different factors.

METHODOLOGY

Several factors influence a person's ability to make decisions during a disaster and the type of decision made. As noted, the type and structure of information provided may differ across different social media platforms. Furthermore, different social backgrounds may influence one's perspective on information shared, and types of important information differ by household. This study, therefore, conducted an empirical analysis of how social, geographic, and disaster characteristics collectively influence a household's: (1) Use activities on social media and different social media platforms, (2) Perceived information reliability, (3) Information sharing; and (4) Information checking. The study approach was designed to examine variations in these four groups of social media use attributes for households across different social, geographic, and disaster contexts. This section explains the study contexts, survey development, data measures, and statistical approaches and models to derive answers to these research questions.

Study Regions

The proposed research questions will be explored in a cross-sectional study of households impacted by hurricanes in the continental United States. Between 2017 and 2018, the Gulf Coast, Carolinas, and the Pan Handle were hit by record-breaking hurricanes. Three separate hurricane events were selected for this study. Each hurricane event has unique characteristics in terms of the storm's intensity, geographic location, and communities, each bringing to the study different contexts to test our research questions.

Hurricane Harvey made landfall along the Texas coast in late August 2017 as a category four storm, impacting all 4.7 million inhabitants of Harris County, the most populous county in Houston and Texas. Widespread and devastating flooding caused by record-breaking rainfall made 22 of Houston metro's significant freeways impassable during, and nearly 300,000 households lost power (HCFCD, 2018).

Hurricane Michael hit the Florida Panhandle and Big Bend region as a Category 5 hurricane. Strong winds and storm surge caused catastrophic damage to buildings, hospitals, and schools (Blake & Zelinsky, 2017). In addition to extensive structural damage, hurricane-force winds caused widespread power outages across the region, where nearly 100% of households across a large portion of the Florida Panhandle lost power, with some of these outages lasting weeks (Blake & Zelinsky, 2017). Inland flooding associated with Hurricane Michael was relatively limited because the storm as the hurricane tracked rapidly across the area (NWS, 2018a). The highest amount of rainfall was observed near Crossroads, GA (Quitman County) at a total of 6.84 inches, with the second-highest amount for the region recorded in Calhoun County, FL, with 6.66 inches (NWS, 2018a).

Hurricane Florence made landfall near Wrightsville Beach, N.C. as a Category 1 hurricane, in mid-September 2018. It was the single wettest hurricane on record for the Carolinas and cost $24 billion (NWS, 2018b). It produced extensive wind damage along the North Carolina coast from Cape Lookout, across Cartert, Onslow, Pender, and New Hanover counties. Thousands of downed trees caused widespread power outages to nearly all of eastern North Carolina. The hurricane produced a record-breaking storm surge ranging from 9 to 13 feet and intense rainfall of 20–30 inches, causing life-threatening flooding. The hardest-hit areas included New Bern, Newport, Belhaven, Oriental, North Topsail Beach, Jacksonville, and Downeast Carteret County (NWS, 2018b).

Household Surveys

Three web-based surveys were developed and distributed to households in the impacted regions via Qualtrics, an online survey panel software company that matches respondent panels with demographic quotas. To represent the vulnerable population groups in each study area, the authors provided quotas created from U.S. Census Bureau data to draw a sample from the study regions based on age, race/ethnicity, income, and health status. All survey participants were required to be 18 years or older who had directly experienced the service disruptions, meaning that these households did not evacuate before the disaster made landfall. Meeting this criterion, 1075 survey respondents were analyzed for Hurricane Harvey, 573 survey respondents were analyzed for Hurricane Florence, and 706 survey respondents were analyzed for Hurricane Michael, combining to a total of 2354 responses. According to power analysis, this is a sufficient sample for conducting inferential statistics that systematically examine associations within the survey data. The purpose of the survey was to collect information on the reliability of social media information and the uses and behaviors of social media users during disaster events concerning geographic characteristics (urban vs. rural), storm severity and characteristics, and population characteristics (race, health condition, income) (Table 9). Having enough demographic diversity in the sample to provide a sound test of the relationships in the correlation analysis is more important than the degree to which sample means and proportions are representative of the study area population (NWS, 2018b).

Data

Upon retrieving the data, survey responses were modified into either binary or ordinal indicators for statistical modeling and analysis of the survey results. We adopted eight socioeconomic variables and eight social media variables shown in Table 9, which summarizes all measures and their original and converted values used for our statistical analysis. The vulnerable populations determined the social groups in disasters.

Household Sociodemographic Factors

Social variables for location, race, education, and health were made into binary variables, where positive values represented their respective target group. Income level groups were converted to an ordinal scale between 1 and 6, where increasing values correspond to higher income group brackets. The storm, education, and urban classification were each coded as binary variables (Table 9). Household sociodemographic characteristics may describe vulnerable groups often at a disadvantage while preparing for, responding to, and recovering from disaster events (Chang et al., 2014).

For this analysis and to maintain consistency with the social vulnerability index (SVI), households have been classified into sub- groups according to reported ethnic identity, health status, and income level. Age was not used as a factor in the analysis due to the biases introduced by the survey respondents representing households, not individuals. The survey did not differentiate between white Hispanic and non-white Hispanics. Additionally, the ‘other’ racial category represents households that identified as mixed-race or ethnicity in addition to Pacific Islanders and Native Americans. Pacific Islanders and Native American households were grouped into the Other category because of the low population samples. Most statistical analyses require sample sizes to be greater than or equal to 10. The income group levels were divided into three brackets (low, middle, high), according to recent census data on median household income in Texas (US Census, 2018). Sub-categories were combined, as shown in Table 9.

Table 9: Household Survey Data Variables

Category	Survey question	Variable name	Survey Response	Data type
Social Media	Did you use social media during the disaster?	Social Media Use	Yes (1)	Binary
			No (0)	
	Which social media platforms did you use?	Social Media Platform Use	Facebook	Categorical
			Twitter	
			Nextdoor	
			Other	
	Which of the following reasons did you use social media for?	Information Type (Information Seeking)	Flooding status	Categorical
			Damages	
			Road conditions	
			Weather forecast	
			Service status	
			Supermarket closures	
	How reliable was the information from social media?	Perceived Information Reliability	Not at all reliable,	Categorical
			Somewhat unreliable,	
			Neutral	
			Somewhat Reliable	
			Very Reliable	
	Did you use social media to share information about the storm?	Information Sharing	Yes (1)	Binary
			No (0)	
Sociodemographic Measures	Which of the following options would best describe your household's race and ethnicity?	Race	Black	One-hot-encoded
			Asian	
			Latino	
			Other	
			White	
	Please specify your household annual income from all sources before the hurricane landed.	Income	>$25K (A)	Categorical
			$25K-$50K (B)	
			$50K-$75K (C)	
			$75K-$99K (D)	
			$100K- $125K (E)	
			$125K+ (F)	
	Did anyone in your household have a mental or physical disability, or chronic medical condition before the hurricane landed?	Health	Disability (Yes-No);	Binary
			Chronic illness (Yes-No)	Binary
	What is the highest education level among your household members?	Education	College Educated & Beyond,	Categorical
			High School Diploma & Equivalent,	
			No H.S.	
			Other	
Geographic Measures	*Based on reported zip code	Hurricane Impact Region	Harvey	Categorical
			Michael	
			Florence	
	*Based reported County	Urban	Yes	Binary
			No (Rural)	

*Asterisk indicated data retrieved outside of the household empirical surveys.

Social Media Use Factors

Social media measures focused on collecting information broadly, on the respondent or respondent's household's use of social media during the disaster, the choice of social media platform, information seeking habits, information checking activity, perceived reliability of the information found on social media platforms. These measures were similarly converted in binary or ordinal indicators where applicable. Response to social media information reliability was converted to a dummy variable for each categorical response (Not at all reliable, Somewhat unreliable, Neutral, Somewhat Reliable, Very Reliable).

STATISTICAL APPROACH

First, univariate statistics of the survey question results were determined and summarized as an absolute frequency concerning each storm event and as a whole (combining all three storm events). Proceeding this step, Welch ANOVA 1-way tests were used to assess the statistically significant differences in household 1) Social Media Use, 2) Social Media Platform Choice, 3) Social Media Information Reliability, and 4) Information Sharing on Social Media across different social and geographic characteristics and storm events, as measured by the eight socioeconomic variables described in Table 1. As the ANOVA test is significant, we also computed Tukey HSD (Tukey Honest Significant Differences) to perform multiple pairwise-comparisons to determine if the mean difference between specific pairs of groups is statistically significant. Results from this analysis component allowed us to formally determine whether or not significant differences in the behaviors and use of social media exist across different population groups. This information informs about whether vulnerable groups are not active on social media during disasters. Some research has used social media data (such as tweets) to determine disparities in social media usage, and their conclusions suggest that because they are not active in social media during disasters based on their metrics, they are at greater risk due to communication gaps (Samuels & Taylor, 2019). The current analysis could confirm whether the reported results based on social media data are valid.

In the next step, multinomial logistic regression models were used to analyze relationships between social media usage and activity and social characteristics in further depth using the multinom function from the net Package in R (Ripley & Venables, 2016). The level of the outcomes that we used as our baseline is specified in Table 9. All analyses were performed using R version 3.6, using α<0.05 as the statistical significance level. The models tested are shown below, according to the variables summarized in Table 9.

Model:

$$\ln\left(\frac{\mathrm{P}\left(\mathrm{Y}_{\mathrm{n}1,2,3}=1\right)}{\mathrm{P}(\mathrm{X}_{\mathrm{n}}=\mathrm{x})}\right)\sim \text{flooding status} + \text{weather forecast} + \text{supermarket closures} + \text{road condition} + \text{damages} + \text{service status}$$

Where X_n = *information type-checked* and Y_{n1} = *social media platform used*, Y_{n2} = *race and ethnicity*, Y_{n3} = *storm event.* The input X_n of this model is a vector with binary values regarding the types of information. This model's output is the probability of the specific social media platform (i.e., Facebook, Twitter, Nextdoor), racial and ethnic groups, and the purpose of information checking during the disasters. Using the storm events as a predictive variable, the outcome of this model will determine the association between storm events and certain information seeking purposes to determine whether or not the purpose of information seeking differs for the storm event.

RESULTS AND DISCUSSION

Survey Results

Table 2A of Appendix A summarizes the survey respondents' socio-demographic characteristics from each storm event. Harvey's subjects had greater ethnic and racial diversity compared to Michael and Florence and had the most significant number of households without a college education or beyond. This distinction is essential in discussing the underlying factors of social media platform uptake to be detailed further into the discussion of the statistical analysis results. The majority of survey respondents used social media during each hurricane event: about 62% of respondents impacted by Michael, 67% from Harvey, and 74% from Florence used some form of social media during the storms (Table 2A, Appendix A). Consistent with reports [84], Facebook was the dominant social media platform for social media users across all three hurricane events (Table 2A, Appendix A).

Results Summary

The research presented in this paper analyzes several aspects significant to understanding the social media use of population groups during disasters. We first present an overview of the key findings from the presented statistical analysis, followed by subsections which detail the statistical results along with a discussion of their implications in existing literature and real-world applications.

Table 10 summarizes the statistically significant results from the analysis of variance (ANOVA) tests across social and geographic location groups and social media characteristics analyzed. The interpretation of these results is presented below using the results of the Tukey

Honest Significant Differences tests. Each cell in the table marked with an "X" signifies a social media characteristic that was determined to have differences when considering different population groups. For an example, Table 10 explains that general social media uptake (S.M Use), Twitter (TW) and Nextdoor (ND) use, and perceived reliability of social media information (Reliability) depends on one's level of educational attainment. Empty cells in the table signify that there is no statistically significant difference in the social media characteristics among different population groups.

Social media uptake was generally uniform across most subdivisions of the population apart from Race and Ethnicity. The only statistically significant difference found from the analysis of variance occurred among White households: they were less likely to be social media users

Table 10: Reported Disparities among population groups according to ANOVA 1-way tests

Reported disparities among population groups concerning social media characteristics according to ANOVA 1-way tests.

Group		Social Media Characteristics						
		S.M Use	F.B.	TW	ND	Info. Sharing	Reliability	Reason for Use
Education		X		X	X		X	
Income			X		X	X	X	
Race & Ethnicity		X	X	X	X	X	X	X
Geographic Location	*Urban*		X	X	X		X	X
	Storm Event			X	X	X		X
Health	*Chronic*					X		
	Mobility Issues		X	X				

*S.M. (Social Media), F.B. (Facebook), T.W. (Twitter), N.D. (Nextdoor).

at all, compared to other racial groups. Facebook is still the most popular and frequently used social media platform (Duggan & Smith, 2013). During Hurricane Harvey, social media users were more likely to be users of multiple platforms than users in Florence and Michael. Interestingly, while statistically significant differences among households of different educational status groups existed, the relationships between education attainment and social media use were not precisely linear. Households with a college degree or higher and households with no degree were more likely than households with a high school diploma to use social media. While this result seems counterintuitive, it is not un- founded in other researchers studying the disparities in social media use across population groups with similar “found patterns” that counter the traditional digital divide (Micheli, 2016; Correa, 2016).

Recent studies on social networking sites (SNS) suggest that because of the wide adaption of social media platforms across all population groups, a users’ social background is no longer a significant predictor of participation or access to social media (Micheli, 2016). While the difference in whether an individual will use social media or not is not significant, the difference is more likely to be found concerning the information seeking and sharing behaviors and actions, as we confirm in this study’s analysis. Social content is more likely to be created by lower-income or racial minorities (Blank & Lutz, 2017). Additionally, different social backgrounds trigger different motivations and methods for the use of social media platforms (Micheli, 2016). Found that Teenagers from ‘lower-income’ families are more enthusiastic about the communication and relational features of these sites while their more elite peers were more interested in the “capital enhancing opportunities” offered by social media platforms and are characterized by limited activity on the platforms to display “a critical stance" (Micheli, 2016).

Respondents in the Harvey-impacted region demonstrated a more diverse use of social media platforms. This can indicate a few connections. First, respondents from the Harvey-impacted region were all classified as ‘urban-dwellers.’ In general research regarding social media users, Urban residents are more likely to be active across other social media platforms, particularly Twitter and Instagram (Perrin, 2019). The broader and more diverse use of social media platforms in the Harvey region is possibly reflective of their urban environment. People residing in urban areas are more likely to be exposed to new technologies and uptake new technologies earlier and quicker than their suburban and rural counterparts. As a result, the broader use may increase the extent of exposure to information surrounding disaster events instead of individuals or households that rely on only one social media platform. Another significant finding was that social media use was less during Michael than both Florence and Harvey. This might be explained by another finding that White households, in general, were less likely than other ethnic and racial groups to be social media users. As other research suggests, social media platforms or social networking sites are more likely to be used by individuals from less-advantaged socioeconomic or cultural back- grounds (Micheli, 2016).

Theme 1: Geographic and Urban-Rural Disparities in Social Media and Platform Uptake

Using an analysis of variance (ANOVA), urban and rural geographic factors were not found to have statistically significant effects on the use of social media during the hurricane events in (F (df = 1, N = 2354) = 0.487, $p = 0.485$). However, statistically, significant differences were observed concerning urban and rural households and the type of plat- forms used by households (Table 10). A posthoc Tukey test showed that households in urban areas were more likely to be active on Twitter and Nextdoor than their rural counterparts ($M = 0.123 \pm 0.034$, $p < 0.001$; $M = 0.095 \pm 0.187$, $p < 0.001$). Similarly, Facebook was not as prominent as a social media platform choice in urban areas ($M = - 0.042 \pm - 0.120$, $p < 0.001$). The extent of social media use was different across households according to the storm event classification (F (2,2351) = 3.951, $p = 0.019$). Using the posthoc test there were fewer social media users among households impacted by Hurricane Michael compared to both Harvey ($M = - 0.103 \pm 0.005$, $p = 0.075$) and Florence ($M = - 0.133 \pm 0.009$, $p = 0.021$). The difference between social media users among households impacted by Harvey and Florence was not statistically significant ($p = 0.660$). Similarly, statistically significant differences were found regarding the platform used (Table A, Appendix A). The amount of Twitter users was statistically significant and greater among households impacted by Harvey than Florence ($M = 0.010 \pm 0.113$ $p = 0.016$), which may indicate the fact that Harvey-impacted areas were all classified as urban. Nextdoor found less use in the Michael-impacted areas compared to that of both Florence and Harvey ($M = -0.149 \pm -0.030$, $p<0.001$;($M=-0.174\pm-0.070$, $p<0.001$).

Recent statistics of Nextdoor use in the United States show that the platform is active in 175,000 neighborhoods across the country, most prominent in its founding location, San Francisco [85]. To date, no publicly available data would reveal regional uptake trends in Nextdoor use to rule out 'hot spot' areas for Nextdoor use. However, Nextdoor likely has more prominence in areas or places where residents feel the need to be more socially connected to their communities or have a sense of belonging. It is interesting to note that the racial and income disparity in the Michael-impacted population was far more significant than the populations surveyed in Harvey and Florence. Considering the finding that Nextdoor users were more likely to be from more educated, White, and higher-income groups, the racial and income gap in the Michael impacted region could be a likely reason for the lack of Nextdoor use during the storm event. Literature shows that residents in rural areas go online less frequently than their urban and suburban counterparts [84]. Nearly three-quarters (76%) of adults living in rural communities re- ported using the internet on at least a daily basis, compared to more than eight-in-ten of those in suburban (86%) or urban (83%) areas. Meanwhile, 15% of rural adults say they *never* go online, compared with less than one-in-ten of those who live in urban communities (9%) and those who live in the suburbs (6%) [84]. If social media becomes the dominant and prominent means for dispersing information during a disaster event, then there are concerns that households in rural areas are at a disadvantage in terms of knowledge collection and having a digital voice.

Theme 2: Sociodemographic Disparities in Social Media and Platform Uptake

Some studies have identified a 'reproduction' of social inequalities and ethnic divisions in the patterns of social media platform adoption displayed by teenagers and young people: the specific social media platforms on which youth choose to create a profile tends to reflect their social class and ethnic background (Micheli, 2016). Sociodemographic variables (parental education, socioeconomic status, and ethnicity) do not explain young people's general use (or non-use) of social media platforms. Rather, they are associated with the particular SNSs they embrace (Hargittai, 2007). One social media platform's choice over another is influenced by a mechanism of distinction that reproduces class and ethnic differences. Below are the statistical results from our study which support existing literature on social class disparities in social media platform use and uptake.

Educational Attainment

Similar to geographic disparities, a statistically significant difference in social media uptake was found across different levels of a household's highest educational attainment level ($F(2,2354) = 5.821$; $p = 0.003$). Interestingly, the relationship between educational attainment and social media use was not strictly linear. Households in which the highest educational attainment was a high school degree statistically significantly more significant in social media use than households that did not have a high school level degree ($M = -0.310 \pm 0.013$, $p = 0.080$). Interestingly, social media users were greater among households whose highest educational attainment was a Highschool Diploma compared to both households without a Highschool diploma and a college degree (Table 5a). Nextdoor users were more common among households with a college degree or higher, with the difference between educational attainment groups being statistically significant compared to the High- school Diploma group (M = − 0.155 ± − 0.048, p = 0.000)**.** Conversely, there was also a statistically significant difference in social media use among households with a college degree or higher and households with only a high school degree, where use was more significant in the latter group (M = 0.020 ± 0.136, p = 0.005). There was no statistically significant difference between the college and beyond and no high school diploma groups ($p = 0.400$).

Racial and Ethnic Groups

A significant difference among racial and ethnic groups concerning social media use was also found (F (2352, 4) = 2.361, p = 0.051). The amount of Facebook users among White households was greater compared to Asian households (M = 0.007 ± 0.325, p = 0.035), while considerably larger compared to Black households (M = − 0.059 ± 0.107, p = 0.068). A higher prevalence of Nextdoor users was also found among White households than Black and African Americans and households of Other race and ethnicity groups (M = 0.022 ± 0.150, p = 0.002; M = 0.029 ± 0.249, p = 0.005). Twitter use was statistically significantly higher among Latino and Black households compared to White households (M = − 0.210 ± − 0.027, p = 0.004; M = − 0.153 ± − 0.029, p = 0.001).

White households were less likely to be social media users overall across all storm regions. Tukey tests revealed that the difference in use was statistically significant compared to Latino Households, which has the greatest use of social media than all racial and ethnic groups, holding all other variables constant. This has significant implications for disaster informatics since most current algorithms used are designed to extract English language tweets or other forms of information only. In areas of high Latino populations, social media information is likely shared or created in Spanish, similarly for other ethnic minorities. There are several limitations for the analysis conducted only on English tweets. One might miss some crucial situational information during disasters when developing algorithms or techniques to detect and map disaster situations. Two, it might misrepresent the Latino population's needs when they are in need or at risk. Hence, multi-linguistic techniques are needed to get a complete picture of disaster impacts and cover all populations' needs at risk.

Income Level

The digital divide is also found for income groups and educational attainment, and even health status (Table 5A, Appendix A). Lower-income households were associated with being Facebook users, where the difference between E and C($M = -0.204 \pm -0.022, p = 0.006$)and F and C ($M = -0.173 \pm -0.017$, $p = 0.001$) were statistically significant. Higher-income households were associated with being Nextdoor users, for all income groups apart from group B were statistically significantly greater than households in income group A (Table 5a). There was not a statistically significant difference among income groups concerning Twitter use ($F(5, 1551) = 0.96$, $p = 0.441$).

Health Status

Households with residents having health problems related to limited mobility were less likely to be Facebook users ($M = -0.092 \pm -0.002$, $p = 0.039$) and 0.094 times more likely to be Twitter users ($M = 0.043 \pm 0.145$, $p < 0.001$). There were no statistically significant differences among households with chronically ill members and social media use or platform use. Literature shows that individuals with mobility difficulties were more likely to be poorly educated, living alone, impoverished, obsess, and having problems conducting daily activities [86]. Con- ducting post-analysis, we observed a positive correlation between households with limited mobility issues and Black and African-American households ($r = 0.09$, $p = 0.012$).

Theme 3: Differences in Information-Seeking Activity

Disparities Across Storm Events

Logistic and general regression models were employed to test for significant relationships between social media information-seeking activity and storm and sociodemographic characteristics. Tables 6–8 of the Appendix A section summarize the estimate coefficients, standard error, odds ratio, and p-value of significance for each indicator and its predictors. Different ethnic groups reported different use-applications for social media during the storms. In general, minorities were less likely to report using social media for information about *Damages* and the *Status of Service Disruptions* during Michael and Florence. Variations in usages by the population became more evident when narrowing down to the choice of platform used by households and using social media during the storms. Racial minorities expressed interest in finding information on supermarket closings on social media.

On Nextdoor, there was a positive correlation between the use of the app and searching for supermarket closings. However, racial minorities were less likely to be users of this platform. Social media users during both Harvey and Florence were most concerned about finding information regarding road conditions and flooding status, while those impacted by Michael were more likely to use social media to check the on-road status and physical damages (Fig 10). This finding indicates an association between storm characteristics and information seeking. From this finding, we can infer the critical characteristics of Hurricane Michael. Given that there was minor inland flooding caused by the hurricane, it makes sense that impacted households did not highly demand information on flooding. Regression models were used to determine the nature of (negative or positive) the relationships between the specific storm impact attributes (information seeking purpose) and the storms themselves (Table 11). The results show that for Michael, households were concerned most with storm damage

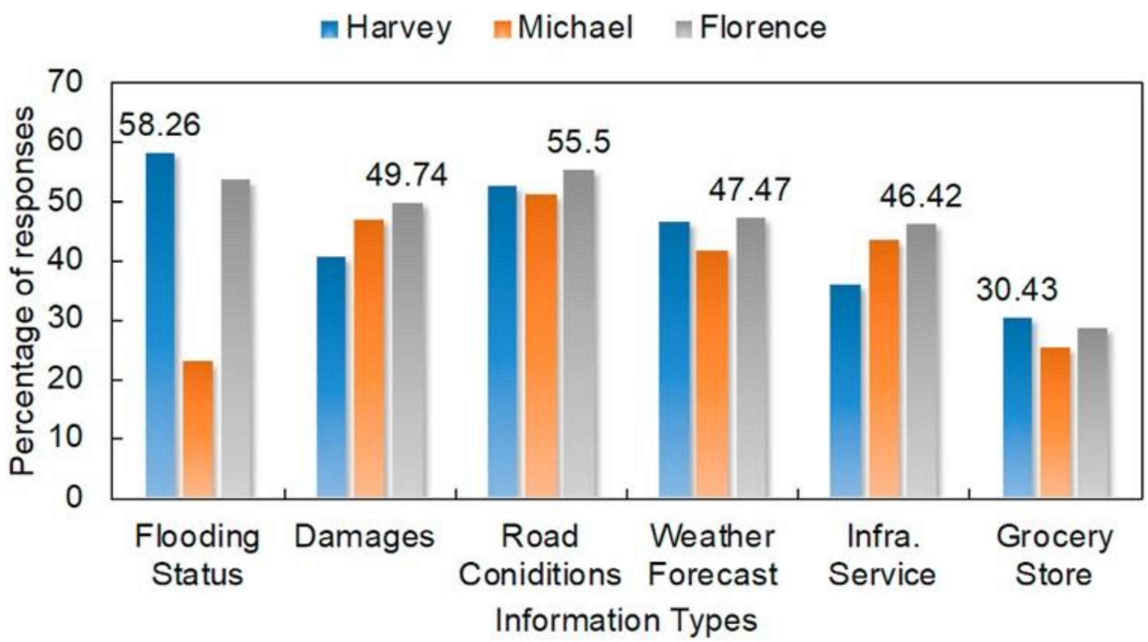


Figure 10: Infrastructure types checked on social media during storms (%)

Table 11: Information checked during storms

Storm	Info. Checked	Estimate	Std. Error	t-value	Sig.
Michael	Intercept	0.321	0.033	9.880	<0.001
	Flooding Status	−0.595	0.027	−22.100	<0.001
	Weather	0.037	0.022	1.660	0.096
	Super Market	−0.014	0.021	−0.639	0.523
	Road Condition	0.019	0.026	0.738	0.461
	Damages	0.149	0.022	6.783	<0.001
	Service Status	0.280	0.038	7.267	<0.001
	Residual standard error: 0.3871 on 1538 degrees of freedom				
	Multiple R-squared: 0.2665, Adjusted R-squared: 0.2636				
	F-statistic: 93.13 on 6 and 1538 DF, p-value: < 2.2e-16				
Harvey	Intercept	0.501	0.038	13.100	<0.001
	Flooding Status	0.511	0.032	16.200	<0.001
	Weather	−0.014	0.026	−0.524	0.600
	Super Market	0.057	0.025	2.270	0.023
	Road Condition	−0.042	0.031	−1.380	0.169
	Damages	−0.189	0.026	−7.320	<0.001
	Service Status	−0.291	0.045	−6.440	<0.001
	Residual standard error: 0.455 on 1538 degrees of freedom				
	Multiple R-squared: 0.171, Adjusted R-squared: 0.168				
	F-statistic: 52.97 on 6 and 1538 DF, p-value: < 2.2e-16				
Florence	Intercept	0.178	0.037	4.890	<0.001
	Flooding Status	0.084	0.030	2.780	0.006
	Weather	−0.023	0.025	−0.934	0.351
	Super Market	−0.043	0.024	−1.810	0.071
	Road Condition	0.023	0.029	0.783	0.434
	Damages	0.040	0.025	1.610	0.108
	Service Status	0.011	0.043	0.260	0.795
	Residual standard error: 0.4351 on 1538 degrees of freedom				
	Multiple R-squared: 0.01291, Adjusted R-squared: 0.009058				
	F-statistic: 3.352 on 6 and 1538 DF, p-value: 0.002759				

($\beta = 0.149$, $p < 0.001$) and the status of infrastructure services ($\beta = 0.280$, $p < 0.001$). Interestingly, the use of social media for information on flooding during Michael was negative ($\beta = -0.594$, $p<0.001$). From this finding, we can infer some key characteristics of Hurricane Michael. Given that there was minor inland flooding caused by the hurricane, it makes sense that impacted households did not highly demand information on flooding. Conversely, Hurricane Harvey is infamous for its disastrous flooding. Households were about three times as likely to use social media to check for updates on flooding ($\beta = 0.511$, $p < 0.001$) but were less interested in information on infrastructure damage ($\beta = -0.189$, $p < 0.001$) or service disruptions ($\beta = -0.291$, p < 0.001). Previous research has found that the secondary characteristics of disaster impact, its duration, scope, and magnitude, influence the extent to which actors utilize social media in disasters [29]. The results of the models explored in this analysis support this finding to an extent. There is a slight significance in Hurricane Harvey and households seeking in- formation about supermarket closures' status (β = 0.057, p = 0.023). Households impacted by Florence were more likely to check for flooding information (β = 0.084, p = 0.006).

Differences Across Social Media Platforms

The relationship between social media platforms and information sought was also explored to determine whether there is a statistically significant difference in platforms' usage purposes. This information can also inform us about the types of information about a disaster present on one social media platform and not another and demonstrates the purpose of the use and role that platforms have during disasters. Certain population groups are more likely than others to use specific platforms than others, therefore it is important to look at the difference in information seeking activity across platforms. It was found that for households using Facebook, Weather, Damages, and Service Status were most often checked (Table 12). For Twitter, only checking for Weather up- dates was statistically significant (β = 0.065, p = 0.047). For Nextdoor Users, Supermarket, Service status, and road closures were positively correlated to the use of Nextdoor (Table 12). However, only supermarket status was statistically significant (β = 0.068, p = 0.041). Prior studies indicate that different racial/ethnic populations display varying internet and social media use trends over time. The use of social networking applications increased across all ethnicities, where English- speaking Latino and African American internet users were on social media platforms at higher rates than White users between 2010 and 2013 (Blume, 2017). Since

2013, English-speaking Latinos' use of social networking websites has been statistically significantly higher than other races [88]. Among Internet users, racial and ethnic minorities regularly access these platforms at higher rates than those of White backgrounds (van Deuresen & van Dijk, 2013).

Table 12: Social media platform and information seeking activity

Table 10
Social media platform and information seeking activity.

Social Media Platform Used	Info Checked	Estimate	Std. Error	t-value	Sig.
Facebook	Intercept	0.787	0.026	30.500	<0.001
	Flooding Status	−0.028	0.021	−1.290	0.199
	Weather	0.061	0.018	3.450	0.001
	Super Market	−0.029	0.017	−1.690	0.091
	Road Condition	−0.015	0.021	−0.729	0.466
	Damages	0.073	0.018	4.190	<0.001
	Service Status	0.065	0.031	2.110	3.492
	Residual standard error: 0.310 on 1538 degrees of freedom				
	Multiple R-squared: 0.026, Adjusted R-squared: 0.022				
	F-statistic: 6.848 on 6 and 1538 DF, p-value: 3.474e-07				
Twitter	Intercept	0.161	0.030	5.410	<0.001
	Flooding Status	−0.012	0.025	−0.487	0.626
	Weather	0.039	0.020	1.940	0.053
	Super Market	0.016	0.020	0.814	0.416
	Road Condition	−0.046	0.024	−1.910	0.056
	Damages	−0.014	0.020	−0.712	0.477
	Service Status	0.007	0.035	0.205	0.837
	Residual standard error: 0.355 on 1538 degrees of freedom				
	Multiple R-squared: 0.005, Adjusted R-squared: 0.001				
	F-statistic: 1.307 on 6 and 1538 DF, p-value: 0.2506				
Nextdoor	Intercept	0.117	0.031	3.820	<0.001
	Flooding Status	0.064	0.025	2.540	0.011
	Weather	−0.057	0.02084	−2.711	0.007
	Super Market	0.062	0.020	3.074	0.002
	Road Condition	0.034	0.024	1.385	0.166
	Damages	−0.050	0.020	−2.200	0.027
	Service Status	0.020	0.036	0.527	0.598
	Residual standard error: 0.355 on 1538 degrees of freedom				
	Multiple R-squared: 0.005, Adjusted R-squared: 0.001				
	F-statistic: 1.307 on 6 and 1538 DF, p-value: 0.251				

While Facebook maintains its spot as the most popular platform, young African-Americans are twice as likely to use Twitter, and Latinos are more likely to engage in instant messaging applications in comparison to Whites [88]. Whereas inequality in online access has begun to decrease, use purposes and 'navigation competence' remain a source of division societally [108]. Variations in usages by the population became more evident when narrowing down to the choice of platform used by households and using social media during the storms. Racial minorities expressed interest in finding information on supermarket closings on social media. On Nextdoor, there was a positive correlation between the use of the app and searching for supermarket closings. However, racial minorities were less likely to be users of this platform. This could imply potential communication and information gaps that would help mitigate hardship and well-being impacts due to a disaster.

Theme 4: Disparities in Perceived Reliability of Information on Social Media

ANOVA 1-way tests were used to determine if vulnerable population groups (Race, Income, Education, Urban/Rural, health condition) were more likely to report information unreliability on social media (Table 11a). Regression was not used in this part of the analysis to allow for a focused assessment of the response to each category. The analysis found that there is a statistically significant difference among income groups their perception of information reliability on social media plat- forms, particularly across the group experiencing *somewhat reliable information* ($F(5,1539) = 4.375$; $p = 0.001$). Each group income group B, C, D, and F were statistically significantly greater compared to group A in experiencing reliable information ($M = -0.001 \pm 0.218$, $p = 0.050$; $M = 0.047 \pm 0.274$, $p < 0.001$; $M = 0.042 \pm 0.301$, $p = 0.002$; $M = 0.142 \pm 0.015$, $p = 0.018$). While not statistically significant, African American households were more likely to report ‘somewhat unreliable in- formation’ compared to White households ($F(4,1540) = 2.43$, $p = 0.046$; $M = -0.093 \pm 0.001$, $p = 0.056$), and neutral ($F(4, 1540) = 5.099$, $p < 0.001$), $M = -0.147 \pm -0.01, 6$, $p = 0.006$). ‘Other’ households were similarly less likely than White households to report Neutral experience with information reliability (-0.229 ± 0.004, $p = 0.038$). White households were more likely than both Black and African American and Other households to have a Somewhat Reliable experience ($F(4, 1540) = 13.15$, $p < 0.001$); $M = 0.130 \pm 0.301$, $p < 0.001$, $M = 0.021 \pm 0.314$, $p < 0.001$). Yet, they are also more likely than White households to report Very Reliable information ($F(4, 1540) = 3.525$, $p = 0.007$, $M = -0.170 \pm -0.008$, $p = 0.022$). Households with a high school education and below were more likely to report highly unreliable information ($F(2, 1539) = 7.62$, $p < 0.001$; $M = 0.001 \pm 0.042$, $p < 0.001$or neutral information (($F(5, 1539) = 3.948$, $p = 0.020$; $M = -0.210 \pm -0.066$, $p < 0.001$). Increasing the highest educational attainment of the household tended to correlate with higher levels of reliability.

These findings have significant underlying implications related to the social connectivity and network of households. According to other studies, the judgment of misinformation and or information reliability narrows down to the level of trust an individual has with the information sharer (Sterrett et al., 2019). This study demonstrates that who shares an article on a social media site like Facebook has an even more significant influence on whether people trust what they see. A trusted sharer has more significant effects on beliefs about the news than a reputable media source (Sterrett et al., 2019). Furthermore, education plays a crucial role in the perception of information from social media. Viswanath (2006) published insightful research on the differential use of social media and information sharing across social groups concerning health information and its correlation to health outcomes in different population groups. Individual characteristics, particularly education status, have a substantial impact on one’s ability or capacity to process and act on information; it provides the necessary confidence, sense of efficacy, and knowledge in enabling someone to navigate complex systems, like disasters (Viswanath, 2006). This is an important finding because machine learning algorithms generally assume uniform usage and social media users' behavior. News consumers often see news filtered through others who share the content rather than directly to the reporting source (Micheli, 2016). This leads to concerns about misinformation infiltrating these networks and spreading across the public sphere. Given the less structured and more participatory information environment, what can we say about people's trust in the news on social media: people are more likely to trust an article on social media if it is shared by a public figure they trust than by one they do not trust (Sterrett et al., 2019). They are also more likely with a trusted public figure sharing news to say they would engage with the article in ways like sharing it or recommending the source to friends or family (Sterrett et al., 2019). If people do not know the originating source, they approach its information similarly to how they would approach sources they know and trust (Sterrett et al., 2019). People's trust in the news they see on social media is strongly related to who shares it.

Theme 5: Disparities in Information-Sharing Across Sociodemographic and Geographic Characteristics

Information sharing through social media was found to be different across the storm events ($F(2, 1542) = 6.334$, $p = 0.002$). Information sharing through social media was more prominent during Hurricane Harvey compared to both Michael ($M = -0.143 \pm -0.008$, $p = 0.023$) and Florence ($M = 0.025 \pm 0.164$, $p = 0.004$)). Similarly, information sharing was statistically significantly higher in urban areas compared to rural areas ($F(1,1542) = 10.12$, $p = 0.001$); ($M = 0.037 \pm 0.158$, $p = 0.002$), Chronic Health problems ($F(1,1543) = 3.197$, $p = 0.074$). No statistically significant differences were found among racial groups ($p = 0.226$), income ($p =$

0.841), mobility health issue groups (p = 0.143), or education attainment groups (p = 0.41). However, ANOVA tests were conducted to assess group difference while controlling for each storm event. The results illustrate a different narrative. During Hurricane Florence, disparities in information sharing were found among racial and ethnic groups (F (4,392) = 3.224, p = 0.013). During Hurricane Florence, households identifying as both Other and White reported more information sharing activity compared to Black and African American households (M = − 0.007 ± 0.357, M = 0.0.046 ± 0.630, p = 0.014). No statistically significant differences were found across other racial and ethnic groups during Florence or Harvey (F (4,704) = 1.709, p = 0.146); (F (4, 434) = 0.700, p = 0.592). During both Hurricane Harvey and Michael, households with chronic health patients were more likely to share information on social media compared to households without a chronic health member (F (1, 437) = 3.042, p = 0.082); M = − 0.011 ± 0.180; p = 0.082).; member (F (1, 707) = 2.881, p = 0.090); − 0.009 0.134; 0.090). No statistically significant differences were found among income groups (F (5, 153) = 0.411; p = 0.840), education (F (2, 1542) = 0.893, p = 0.410), mobility (F (1, 1543) = 2.148, p = 0.134).

Information sharing through social media was more prominent during Hurricane Harvey compared to both Michael and Florence. It is not possible to conclude whether this is due to more extensive damages or impact from the survey information. Other possible explanations can be related to the communication network disruptions, connectivity, and strength of households' social ties, which was not included in this analysis. In general, there were no significant variations in information sharing among different population groups. However, White and Other racial and ethnic households were statistically more likely to have shared information compared to Other racial or ethnic groups in Hurricane Florence. During Hurricane Harvey, Black households were found to share more information than other groups; however, the difference was not statistically significant. During Harvey and Michael, households with chronic health patients were more likely to share information on social media compared to households without a chronic health member. This is a significant finding as it contradicts studies using digital trace data from social media, which have found certain population groups in communities to be underrepresented during disasters (Samuels & Taylor, 2019). Further- more, this can indicate that they had a greater need for information (about healthcare facilities, etc.) and utilized social media for information seeking. Examples of using social media platforms for emergency help were well-documented during Hurricane Harvey. This is a significant bias to address in future work using social media data to analyze different disaster phenomena.

As noted, different platforms have different features that influence the type and format of information shared. While studying disaster impact disparities, the concern is regarding communication and/or knowledge gaps that exist in communities due to gaps in social media use and platform. Another significant phenomenon of social media assessed in this study was the act of information sharing; vulnerable population groups were less likely to report using social media to share information, except for households with chronically ill household members. On the other side, it is apparent that households used social media as passive users, meaning that they used the platforms to collect information about the storm instead of sharing information. Under- standing the usage of social media and the platforms used by households to gather and share information during disasters helps identify the population needs, the most efficient platforms for sharing information, and ensuring it is dispersed to the right audience. With respect to ma- chine learning algorithms and techniques for disaster informatics, the results highlight discrepancies in the outcomes of these models. Blank (2013) observed that sharing ‘social and entertainment content’ online is influenced by income, but with an inverse pattern to what we might expect: users with higher incomes produce less content online (Micheli, 2016). Education is only moderately associated with the use of SNSs; those without high school education are more likely to use SNSs than high school graduates (Haight et al., 2014). A nationwide survey in the U.S. showed that individuals of lower socioeconomic status are more frequent users of Facebook than those of higher status (Duggan et al., 2014). Teenagers whose parents hold a high school diploma are more likely to use SNSs than those with college-educated parents (Ahn, 2011).

This information can give insight into the needs and priorities of different population groups during a disaster. Prior studies indicate that different racial and ethnic populations display varying internet and social media use trends over time. Moreover, between 2010 and 2013, the use of social networking websites increased across all races, with English-speaking Latino and African American Internet users accessing social media platforms at higher rates than White users. Since 2013, English-speaking Latinos' use of social networking websites has been statistically significantly higher than that of other races (Blume, 2017). While the gap access to the internet is quickly closing, the use purposes and internet literacy remain a source of social division (van Deursen & van Dijk, 2013).

CONCLUSION

This paper explored the relationship between population groups and their behavioral patterns related to using social media during disasters. The analysis in this study is conducted in the context of three primary disaster events, Hurricane Harvey, Florence, and Michael. A robust empirical understanding of social media users' characteristics and their activity on social media platforms during disaster events is essential for addressing the digital divide and equitable resilience. Social media is becoming a key platform for information dispersion during disasters;

therefore, any disparities or gaps in the use can lead to gaps in communication and understanding of disaster impacts. From the exploratory analysis presented in this paper, it is clear that social and location factors play significant roles in the uptake of social media platforms and the determinants of information seeking and information sharing during disasters. Results from this analysis confirm the following: (1) Socioeconomic factors along with location and regional effects play a role in determining not only platform uptake but both motivations for information seeking and the action of information sharing on social media, (2) The type of social media platform influences the type of information people seek, (3) Households from lower socio- economic and minority backgrounds were more likely to use social media platforms to seek out different information on social media than their peer, (4) perceptions of information reliability are also influenced by social divides, where households in rural areas, lower- income groups, and racial minorities were more likely to report greater unreliability in social media information. These findings provide a deeper empirical understanding regarding social media usage and differences among various sub-populations for information seeking and sharing during disasters.

This study's findings provide important insights for practice related to information communication in disaster management and intend to inform advanced data mining methods of social media data. First, this study identifies the geographic and population disparities of using social media, which may lead to unequal information access and situation awareness. This signifies that different people have various levels of capabilities to resist the negative impacts of disasters. Existing disaster management does not consider such disparities and may cause unequal resource allocation and relief supports. Second, different people require different types of information by using social media. Based on such understanding, social media platforms can distribute different in- formation to different groups of people to enhance their accessibility of certain types of information. First responders and relief organizations can also use social media platforms to share the information needed by people to enhance their situational awareness in disasters. As discussed in the literature review and introduction, the increasing use and reliance on data from social media platforms in data mining and machine learning models require techniques that are “discrimination-aware” (Faveretto, et al., 2019).

From the presented analysis, we have uncovered several key disparities related to sociodemographic and geographic factors in the social media users, their purpose for using social media during disasters, and perception of information shared across the platforms. Therefore, the empirical findings of this study can guide the development of algorithmic models that consider such biases. For example, developers may opt for specific pre-processing methods that omit possible bias to prevent the new model from learning discriminatory behaviors (Favaerreto et al., 2019). Furthermore, in developing models and data mining, there is a need to “keep the human in the loop.” Humans have a critical role in providing insight, guided by empirical research, for improving fairness in model outcomes (Favaretto, et al., 2019).

ACKNOWLEDGMENTS

The authors would like to acknowledge the National Science Foundation’s funding support under grant number 1846069 and National Academies’ Gulf Research Program Early-Career Research Fellowship. Any opinions, findings, conclusions, or recommendations expressed in this research are those of the authors and do not necessarily reflect the funding agencies’ view.

CHAPTER IV: STUDY 3 - ASSESSMENT OF HOUSEHOLD-LEVEL FOOD-ENERGY-WATER NEXUS VULNERABILITY DURING DISASTERS[§]

OVERVIEW

Water, energy, and food systems are highly interconnected, where disruptions in one system have direct or indirect impacts on others. Little has been studied regarding the nexus interactions at the household level, let alone in a disaster setting. Measuring household vulnerability to their disruptions is an important determinant of resilience and societal risk in the face of natural hazards. This study proposes a new framework based on disaster risk theory and Food-Energy-Water (FEW) Nexus systems thinking to analyze the collective influence of integrated infrastructure disruptions and socioeconomic factors on household vulnerability during disasters. ANOVA one-way tests are used to determine the disparity in disaster risk measures across non-vulnerable and highly vulnerable households. Structural Equation Modeling (SEM) is employed to test the proposed relation- ships between infrastructure disruptions, urban attributes, household preparation behaviors in the context of the 2017 Hurricane Harvey in Harris County, Texas. Overall, the pre-existing conditions of communities in terms of its physical attributes, preparation behaviors, and the coupled durations of FEW infrastructure disruptions were each found to have statistically significant associations with heightened household vulnerability to FEW

[§] Submitted as a journal article in Sustainable Cities and Society as: Dargin, J., Berk, A., & Mostafavi, A. (2020). Assessment of household-level food-energy-water nexus vulnerability during disasters. Sustainable Cities and Society, 62, 102366. doi:https://doi.org/10.1016/j.scs.2020.102366 service disruptions. Physical attributes (β=0.134, p=0.001) and prior experience with disasters (β = -0.103, p = 0.000) were found to be the most significant indicators of poor preparation behavior. households with children, racial minority status, and low income and educational attainment of households were associated with having lower levels of preparedness. The framework developed in this study can serve as a foundation to expand the transdisciplinary research of infrastructure and community resilience to better address the needs of the population in an emergency.

INTRODUCTION

Water, energy, and food infrastructure systems are essential for contributing towards and maintaining the wellbeing of households sheltering-in-place during disasters. The cross-sector interdependencies inherent to these systems make them highly susceptible to physical disruptions, and as a result, have the potential to transform a natural hazard, like a hurricane, into a disaster of cascading events. For example, the energy infrastructure systems provide essential power and fuels upon which most critical infrastructure sectors rely on to operate (FEMA - U.S. Department of Homeland Security, 2017). Damages to food, energy, and water infrastructure systems can lead to water scar- city or contamination, while lack of the quality provision of water, sanitation, health care, food, and transportation services affects the capacity of urban residents to recover and affect households' health and well-being (Dong, Esmalian, Farahmand, & Mostafavi, 2019; Dong, Wang, Mostafavi, & Gao, 2019; Najafi, Peiravi, & Guerrero, 2018; Baker, 2012; Dominianni et al., 2018; Rasoulkhani, Mostafavi, Sharvelle, & Cole, 2019; FEMA - U.S. Department of Homeland Security, 2017;). Similarly, poor solid waste management can cause blockages to stormwater and sewage networks which can lead to waterlogging and flooding (Naik, Kominers, Raskar, Glaeser, & Hidalgo, 2015).

In the aftermath of a disaster, the resiliency of a city relies on the functioning of complex and interdependent infrastructure systems, both soft and physical (Chang et al., 2014). Infrastructure systems must be designed to not only continue functioning under hazardous conditions (Chang, et al., 2014; Godschalk, 2011) but also to provide equitable services to the community (Batouli & Mostafavi, 2018; Davis, Mostafavi, & Wang, 2018). Resilience planning and emergency management require policymakers and agency leaders to make difficult decisions regarding which at-risk populations should be given priority in the allocation of limited resources (Kontokosta and Malik, 2018). Neglecting to include people who rely on certain infrastructure services to support or sustain life and wellbeing, disproportionately places these segments of the population in a higher category of risk and increases their likelihood of requiring rescue and response requirements in the event of a disaster (FEMA - U.S. Department of Homeland Security, 2017). In certain communities, marginalized populations are more likely to depend on public transportation services for daily needs (Jiao, 2017). Inadequate transportation in general sets barriers to financial and job stability (Ewing et al., 2015), as well as healthcare services (Syed et al., 2013). Households living in urban areas known as “food deserts” could be more vulnerable to disruptions in FEW nexus re- sources in disasters (Alwitt and Donley, 1997). Also, disasters may lead to the emergence of new food deserts in urban areas (Walker et al., 2010; Cummins, 2002), all the while the impacts of FEW resource disruptions may be more severe on vulnerable populations such as older adults (Biehl et al., 2017). Kontokosta and Malik (2018) found that resilient neighborhoods were shown to better withstand disruptions to normal activity patterns and more quickly recover to pre-event functional capacity.

The literature on infrastructure interdependencies continues to focus on systems engineering approaches that aim for system optimization while neglecting the concept of resilience

(Chang et al., 2014). Examples of these approaches include the use of computer-based simulation models of infrastructure systems and their linkages (Rasoulkhani & Mostafavi, 2018; Dueñas-Osario, 2007; Min et al., 2007) and analytical models that characterize interdependencies and identify key vulnerabilities, particularly from terrorism threats (Haime and Jiang, 2001, Apostolakis and Lemon, 2005). Haraguchi and Kim (2016) analyzed the impact of Hurricane Sandy from the perspective of interdependence among different sectors of critical infrastructure in New York City, finding that the electricity sector was the key sector to propagate risks to other sectors. Most initiatives to increase the resilience of critical infrastructures in New York City after Hurricane Sandy focused primarily on building hard infrastructures to decrease direct damages, disregarding social dimensions prevalent in the disaster frameworks. It is proposed that switching towards a decentralized scale of operation by decoupling infrastructure systems will help reduce the vulnerability of both the physical and social systems (Stringer et al., 2014) in day-to-day life and in face of disasters. The Food-Energy-Water (FEW) nexus is championed as an approach for attaining sustainable development agenda (Terrapon-Pfaff, Ortiz, Dienst, and Gröne (2018)), and countering the impacts of climate change Blumenfeld et al. (2017) and to reduce system interdependencies and increase system resilience (Daher & Mohtar, 2015). Cross-sector collaboration, as emphasized by the FEW nexus approaches can collectively build community resilience (Miller, 2015). In decentralizing infrastructure system services, essential services can continue to be provided while minimizing the demand for and reliance on emergency services (Miller, 2015). While there are various approaches to FEW nexus applications reviewed by Endo et al., 2015, these simulation models also tend to focus on physical aspects of the supply side of resources, leaving out the critical analysis of the social and behavioral elements of FEW resilience. Furthermore, studies involving the FEW nexus are centralized in historically water-scarce or arid regions, which do not capture the context of natural disasters that typically have sudden onsets like hurricanes, tornadoes, and earth- quakes. One exception is a study carried out about Stringer et al. (2014), which combined the nexus approach with resilience thinking resulting in a multiscale framework aimed at understanding the factors that shape equitable and just outcomes. However, the existing frame- work was not developed in the context of disasters and natural hazards and does not empirically demonstrate or implement the model.

FEW Nexus and disaster resilience research have generally over- looked the disparities that exist in the experience and impact that disruptive events have on marginalized and vulnerable population groups (Stringer et al., 2014). Studies in both disaster and infrastructure interdependencies also tend to focus on broad-scale impacts as opposed to analyzing problems at the household-level, the unit at which infra- structure system services are consumed, and do not consider the bi- directional relationship of the built environment and social systems. Several recent approaches have been developed to quantify the resilience of physical infrastructure systems, namely water supply systems (Balaei et al., 2020), the interconnection between stormwater drainage systems and road transport systems (Yang, Thomas Ng, Zhou, Xu, & Li, 2020), and a resilience index for power distribution systems (Najafi et al. (2018). However, these methods do not directly account for fac- tors and measures of social systems. Methods which did consider aspects of community resilience with the inclusion of social factors include a quantitative framework that models recovery patterns of economic activity in a natural disaster (Qiang et al., 2020), and a social network analysis (SNA) model for characterizing community resilience during different disaster stages, focusing primarily on the role of social capital in shaping resilience (Cui & Li, 2020). These studies do not consider the connections to infrastructure service disruptions experienced at the household level. Kontokosta and Malik (2018) assessed neighborhood resilience capacity during emergencies and disasters by developing an index based on a neighborhood's proximity to certain infrastructure services. While they considered both physical and social infrastructure systems in their study, they did not consider the inter- actions between systems. Cariolet et al. (2019) reviewed existing approaches for mapping urban resilience, finding that most approaches are analytical and not integrate systemic properties of resilience, and thus, highlighting the need for more systematic studies of resilience. It is suggested that the modeling and mapping of subcomponent and sub- systems are sufficient for understanding urban resilience due to the great complexity in mapping urban resilience in its entirety (Cariolet et al., 2019).

From the discussion of existing methods and studies on infra- structure resilience modeling, and community and disaster resilience, the knowledge gaps in the pathway between external factors and household vulnerability (Ge et al., 2017) become evident. As a result, a system-level understanding of household processes related to demand and access to FEW resources during disasters concerning differential household experiences remains limited (Dargin and Mostafavi, 2020; Hussein et al., 2017). The interdependencies among not only critical infrastructure systems but the interdependencies with related institutions are poorly understood (NIST, 2016) as a result of this limitation. In-depth knowledge of the links between cities' characteristic features or urban attributes, related systems, and disasters is indispensable for addressing the root cause of physical and social vulnerabilities as well as for mainstreaming risk reduction into urban planning and management (Wamsler and Brink, 2016). Understanding the integrated relationship of these factors is important for the foundation of planning resilient cities.

Combining disaster risk theory and Food Energy Water (FEW) Nexus systems thinking, this paper presents a new framework for assessing the collective influence of integrated infrastructure disruptions and socio- economic factors on the vulnerability and resilience of households during a hurricane event. Using empirical data from a household survey on disaster experience and infrastructure disruption in Harris County, Texas during Hurricane Harvey in 2017, zip-code areas of high and low FEW infrastructure disruptions were determined. ANOVA one-way testing is used to determine the disparity in disaster risk measures in households across areas of differential infrastructure disruption impact. Structural Equation Modeling (SEM) is employed to test the proposed framework and its associative pathways between infrastructure disruptions, urban attributes, and household preparation behaviors based on the disaster risk measures most associated with households in FEW nexus disruption hotspots. The results of the model intend to build an empirical understanding of the interdependencies among urban FEW nexus systems and households in the context of disasters from the consumption perspective. This study and its findings have multiple novel scientific and practical contributions to both the fields of infra-structure and disaster resilience. In particular, the results of this study allow us to understand, (1) the urban attributes and disaster characteristics influence the sensitivity of vulnerable populations to FEW system disruptions, (2) nature and the extent to which inter- dependencies among urban food, energy, and water systems influence a households' demand and access to these critical resources during extreme weather events, (3) the cascading effects of disruptions in one system of FEW nexus on households' demand and access to resources from other systems, and (4) the behaviors that directly and indirectly influence the extent to which households are impacted by FEW disruptions.

This paper will continue with a review of existing approaches in infrastructure system interdependencies, disaster risk management, and recovery along with their shortcomings. A conceptual framework is introduced as a means for integrating these disciplines addressing the critical research gaps in our understanding of household vulnerabilities to infrastructure disruptions during disasters. The following sections discuss the methodological approach and implementation of the conceptual framework in the form of a structural equation model using empirical data collected from households in Houston, Texas on their experience with Hurricane Harvey in 2017. The paper is concluded with a summary of the results followed by a discussion of the key findings and conclusions.

CONCEPTUAL FRAMEWORK

A number of critical infrastructure dependencies contribute to the interconnectedness of risk to communities during disasters (Wamsler & Brink, 2016), such as Water, Energy, Food, and Transport. By definition, a critical dependency is “a dependency that is crucial for societal functions to work” (Wamsler & Brink, 2016). While it is common to see disasters as “causes”, and the destruction of the built environment as “effects”, the conceptual framework described here on out demonstrates that the nexus between cities, in terms of its physical infra- structure and social systems, and disasters have a bidirectional relationship, which constantly shapes, and is shaped by, both internal (social inequality) and external (climate change) processes. The Household FEW-Disaster Framework builds on prior frameworks of disaster risk and infrastructure nexus, discussed in the literature review to look at the interactions between infrastructure systems. It pays particular attention to the three fundamental components of disaster risk models: hazard, vulnerability, and exposure. Measures of that define physical attributes of urban areas and measure defining household preparation behaviors, and social characteristics and impact of infra- structure disruptions are used to examine the relationship between FEW vulnerabilities and social and physical vulnerability of households. Each subcomponent of the conceptual framework is depicted in Fig 11 and is detailed accordingly in the subsequent sub-sections.

Disaster Risk

Disaster risk is typically defined as a linear relationship (Alexander, 1991) and guides the development:

Hazard × Vulnerability [× Exposure] = Risk → Disaster

Modern definitions of disaster risk connect with the resilience and climate change adaptation agendas. It also responds to the imperative of sustainability (Alexander, 2012). Alexander proposes a new theory of disaster risk, where consequences or impacts of the disaster are influenced by human-vulnerability which is a factor of cultural, physical, and historical accounts. (Alexander, 2012; Zhu et al., 2017). The Pressure-and-Release (PAR) framework, the Hazards-of-Place (HOP) framework, the Exposure-Sensitivity-Resilience (ESR) framework, and the Bogardi-Birkmann-Cardona (BBC) framework are four of the most popular disaster-risk frameworks in the field and literature. The frameworks generally take into account the consequences of direct physical impacts (exposure and susceptibility) as well as indirect consequences (socio-economic fragility and lack of resilience) of a potentially hazardous event. Within each category, the vulnerability factors are described with sets of indicators or indices (Ciurean et al., 2013). Thomas et al. (2019) emphasize that vulnerability is multi-dimensional and differential. Hence, this study examined various factors influencing differential vulnerability among households while facing FEW nexus disruptions in disasters.

Household Vulnerability

Reported household-hardship experienced due to disruptions in the FEW infrastructure system services is used as a proxy for measuring vulnerability in the framework and the survey.

Hardship is generally distinguished from vulnerability by a temporal difference, where hardship is often used to define an experience of the present, while vulnerability indicates a risk of experiencing future hardship (Adelman et al., 2015). Concerning the proposed conceptual framework, there- fore, the authors assume that experienced hardship due to infra- structure service disruptions is indicative of being vulnerable to additional impacts. In theory, there should be indirect relationships between the disruptions and hardships for non-corresponding disruptions. For example, a household may face more food hardship if their power went out for a significant amount of time and the food inside their fridge spoiled. The next question the framework attempts to answer is the extent that certain preparation behavior affects the house- hold's vulnerability, and to what extent access to infrastructure before the storm affected their ability to prepare. The proposed framework allows us to look at vulnerability from physical and social perspectives while highlighting which behaviors and characteristics might trigger individual and collective vulnerability of the FEW nexus systems. Vulnerability is a function of physical disruptions, urban attributes and characteristics, and household behavioral attributes, consistent with preexisting disaster risk models. The vulnerability for each sector of the FEW Nexus is defined by the presence of disruption, while overall nexus vulnerability is defined by the level of hardship a household faced.

Description of the Pathways and Links

The conceptual model presented here will ultimately be tested using empirical data from a household survey and through the development of a structural equation model (SEM). In the construction of this model, there are defined pathways that represent different causal relationships. These pathways are the following: Physical attributes and behavioral socio-cultural aspects are directly linked to the physical/spatial features of a city. For example, high population density, overpopulation, lack of affordable space, and the lack of green and recreational areas can influence family structures, social cohesion, and the sense of community (Wamsler & Brink, 2016). In overcrowded conditions, issues such as competition for space and poor infrastructure (e.g. lack of, or leaking wastewater pipes) can generate conflicts between neighbors. Likewise, the failure of infrastructure to provide adequate water, sanitation, drainage, roads, and footpaths increases the health problems, workload, and insecurity of residents, especially women (IFRC, 2010; Tacoli, 2012). Inadequate transportation infrastructure forces citizens to cross insecure areas (Amnesty International, 2010; Tacoli, 2012). Also, difficult access to urban areas, together with a lack of public leisure space, can isolate certain groups (such as the elderly and women with small children) and make them even more bound to their compact homes (Wamsler & Brink, 2016). Each group of attributes is explained in the following sub-sections.

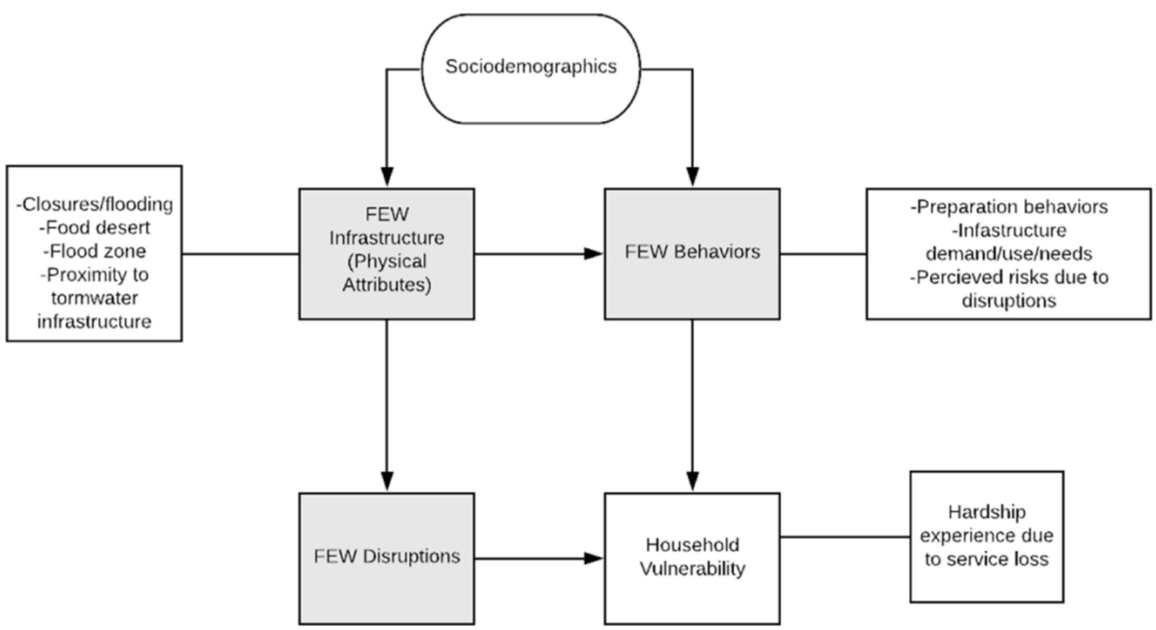


Figure 11: FEW nexus-Disaster Framework: the grey-shaded boxes represent the factors contributing to the vulnerability of households during disasters. Measures of these factors are defined in their respective connected boxes. The lines with arrows signify the direction of the relationships between each factor.

Urban/Physical Attributes

Many social scientists argue that society determines the changes in the physical city (Naik et al., 2015). Physical space has the potential shape social characteristics, by documenting that neighborhoods contain fewer minorities when regulations prevent the construction of multi-family housing neighborhoods (Resseger, 2013; Naik et al., 2015). The most famous hypothesis connecting urban perception and human behavior is the Broken Windows Theory (BWT) of Wilson and Kelling (1982), now used to describe how urban disorder can trigger disorderly behavior (Naik et al., 2015). Other studies have linked socioeconomic characteristics to the built-environment, showing the demographic minorities and low-income households are more likely to reside in closer proximity to hazardous areas, such as toxic waste facilities and industrial facilities (Bullard et al., 2007). Lambert and Boerner (1995) find that housing values grew less rapidly in locations where there was at least one waste site, and percent minority increased more rapidly in these locations than it did in other neighborhoods. Hersh (1995) found evidence that both White and higher-income households tend to leave neighborhoods after industrial plants and waste facilities were constructed, while minorities were more likely to move into these more polluted areas (Gray and Shadbegian, 2010).

Community water systems serve approximately 96 % of the US population (EPA, 2013) however since water utility companies are not required to collect information on their customers, it is difficult to assess social inequities in service provision (EPA, 2013), as it the case with other infrastructure services. Despite the dearth of data in this realm, studies have drawn empirical evidence of social inequities related to water infrastructure services: studies have documented limited access to clean water in low-income communities of color (VanDerslice, 2011). Only 3 studies explicitly examined differences in water infra- structure by income or race in areas served by community water systems. In each of these studies, US Census demographic data for a geographic area (i.e., census block groups, zip code, county) were linked to aggregated water quality or violation data from the community water systems serving that area. The location and use of inferior quality construction materials for building homes are cited as variables that contribute to a vulnerable household's heightened vulnerability during disasters (Bergstrand et al., 2014; Baker, 2012). Another interesting phenomenon related to urban connectivity and system attributes and vulnerability is the design of water drainage infrastructure in systems: the development of drainage infrastructure in more affluent communities often diverts flooding problems downstream, usually less affluent communities (Parkinson, 2003)

Existing studies that look at the intersection of social vulnerability to natural hazards, particularly flooding events, do not include neighborhood or urban characteristics beyond population density and transportation. The physical attributes highlighted in this study are those relevant to FEW systems and their role in pre- and post-disaster. Physical attributes include food deserts, flood zones, proximity to stormwater infrastructure, and environmental hazards. The physical attributes selected in this study are summarized in Table 13 in the next section. These attributes are selected because of their roles in social inequity landscapes and stormwater mitigation, which are significant in the face of hurricanes. In the framework, it is shown that physical at- tributes are influenced by socio-demographics, which influence the risk of FEW disruption impacts. Secondly, the physical attributes influence behaviors and consumption of FEW resources at the household level. There are numerous characteristics of current urban planning and development that drive vulnerability. Human processes such as urbanization and structural defenses (e.g., levees, dams, sea walls) have a large influence on the movement and severity of flooding, ameliorating impacts in some cases, but amplifying them in others (Rufat, Tate, Burton,

& Maroof, 2015). Poorly planned and managed urban development has generated new hazards and extensive risk (UNISDR, 2013). The growing concentration of people and assets in high-hazard areas, along with the marginalization of the urban poor in particularly unsafe areas drives exposure to disaster impact. The most vulnerable groups tend to settle and build homes in unsafe locations that are without adequate provision of infrastructure and critical services (Mechanic and Tanner, 2007). It was theorized that households from historically underrepresented minorities would experience more inaccessibility to food infrastructure, making it more difficult to prepare and exacerbating hardship during the storm. For example, Najafi, Ardalan, Akbarisari, Noorbala, and Elmi (2017) showed that a household is less likely to prepare if they do not perceive that they have the means to; therefore, a high negative correlation between food insecurity was expected, especially in highly vulnerable populations.

Table 13: Survey Measures, Study 3

Framework Component	Variables adapted from survey	Indicator
Physical Attributes	Food Desert	Distance to closest grocery store (miles)
	Living Proximity to stormwater infrastructure	Binary Yes – 1, No - 0
	Living proximity to FEMA flood zone	Binary Yes – 1, No - 0
	Perceived disruption risks	Likert Scale 1-5 (No risk at all – severe risk)
	Health and Social Services	The 2019 SocioNeeds Index - 1-5 (increasing values correspond to areas with higher disparity in health outcomes and services)
FEW Household Behaviors	Preparation actions	Binary Yes – 1, No - 0
	Perception of preparedness	Likert scale 1-5 (overprepared – not at all prepared)
	# of days spent in preparation	# of days
	% of households with Power backup	Binary Yes – 1, No - 0
	% of households reporting use of Power for food	Binary Yes – 1, No - 0
	% of households reporting use of Roads for food and water	Binary Yes – 1, No - 0
	% of households reporting use of Power for health	Binary Yes – 1, No - 0
	% of households reporting use of Roads for health	Binary Yes – 1, No - 0
	% of households reporting use of Water for food	Binary Yes – 1, No - 0
	% of households reporting use of Water for health	Binary Yes – 1, No - 0
FEW Disruptions	Days of water disruptions	# of days of disruptions reported
	Days added to commute	# of days of disruptions reported
	Days of fuel shortage	# of days of disruptions reported
	Days of food disruptions	# of days of disruptions reported
	Days of electricity outage	# of days of disruptions reported
FEW Vulnerability	Water Hardship	Likert scale 1-5 (None at all – A great deal)
	Food Hardship	Likert scale 1-5 (None at all – A great deal)
	Power Hardship	Likert scale 1-5 (None at all – A great deal)
	Transportation Hardship	Likert scale 1-5 (None at all – A great deal)
Sociodemographic Characteristics	Minority – (White – non-White)	Binary Yes – 1, No - 0
	Income	Scale 1-7 (less than $25,000 – more than $125,000)
	Health – Chronic	Binary Yes – 1, No – 0 (any member in household with chronic health condition)
	Health – Disability	Binary Yes – 1, No – 0 (any member in household with a disability)
	College Educated	Binary Yes – 1, No – 0 (any member in household with a college degree or higher)
	Children Under 10 years	Binary Yes – 1, No – 0 (any member in household with children under 10)
	Elderly residents	Binary Yes – 1, No - 0 (any member in household with elderly resident(s))

Household Behaviors and Characteristics

There is recognition that the physical environment can influence human behavior and sociodemographic characteristics of a neighbor- hood (Raman, 2010; Handy, Boarnet, Ewing, & Killingsworth, 2002). Processes involving characteristics such as race, gender, age, and in- come are principal drivers of a population's ability to prepare for, respond to, and recover from damaging flood events (Rufat et al., 2015). Alexander, 2012Alexander (2012) argues that perception and culture are also significant factors of disaster vulnerability. Other important drivers that are not directly addressed in the framework include coping capacity, land tenure, and governance. While these studies focused on neighborhood levels, the household is the fulcrum and most simple unit of measure in which FEW resources are consumed and disruption in FEW systems affects household well-being. Households are the smallest decision-making units and likely to be exposed to external turmoil. This is why in the framework ; household behaviors are influenced by the environment (physical attributes) and sociodemographic characteristics of the household. Waitt et al. (2012) produced "three core dimensions of sustainable household capability" which can be implemented to identify household resilience and are adapted in the framework: "household practices" (preparation actions taken to save or improve the household system); "household structure" (demographic, physical and economic features); "household sustainability judgments" (knowledge, awareness, concerns toward externalities). In this model, sustainability judgments are represented by the perceived risk of the disaster. The sociodemographic background was included in the framework as an overarching effect on vulnerability factors. The general population's experience with extreme weather and disasters is also an important component of both disaster resilience and FEW resilience. Most households do not prepare for disaster until it hits (Najafi et al., 2017), increasing their risk to FEW vulnerabilities.

FEW Infrastructure Disruptions

Disruptions are characterized by a direct and lasting impairment to a dependent activity (Wamsler & Brink, 2016). Disruptions are defined by the presence of a failure or interruption of a service and its duration. For the scope of this paper, food infrastructure is represented as food service and supplies at grocery stores. Water infrastructure refers to drinking water supply and stormwater infrastructure. The energy infrastructure is represented by electricity, fuel, and transportation (roads). Disruptions are triggered by external events, in this case a natural hazard (hurricane). The extent of disruption, however, is determined by physical attributes and household behavioral attributes.

METHODOLOGY

Study Context

The study is centered around the FEW nexus infrastructure outages affecting Harris County residents during Hurricane Harvey (Fig. 11). Hurricane Harvey was a Category 4 storm that made landfall in Texas on August 25th, 2017. Harvey led to severe rainfall and mass flooding throughout the state, impacting all 4.7 million inhabitants of Harris County, the most populous county in Houston and Texas. Record- breaking rainfall wreaked havoc on Houston's infrastructure systems and households making it one of the costliest disasters in U.S. History, after Hurricane Katrina. All 22 of Houston metro's major freeways were flooded and impassable during the storm while nearly 300,000 house- holds lost power (HCFCD, 2017). The proposed framework is used to draw on the causal pathways of risk disparity due to infrastructure service disruptions within a population. The survey design, data measures, and analytical approach are described. Moreover, we utilize empirical data from Hurricane Harvey to test the proposed framework in answering the proposed research questions in the context of critical infrastructure system disruptions due to disaster. The focus of this re- search is on households sheltering in place during a disaster; this discretion, therefore, excludes households that evacuated before Harvey's landfall. Harris County was selected particularly because mandatory evacuation orders were not issued to its residents. Within Harris County, only one city issued a voluntary evacuation order (WFFA, 2017). Several coastal counties along the Gulf Coast were ordered to evacuate which would have made these counties inadequate for our study. The rationale for this selection was that, for the people who evacuated and had to move to shelters or other places, the relevance of infrastructure service disruptions becomes of secondary importance since they have already lost their shelter (the primary place in which infrastructure services are utilized).

Survey

A web-based survey was deployed between April and May 2018 through Qualtrics, a survey company that matches respondent panels with demographic quotas. To represent the vulnerable population groups in the study area, the authors provided quotas created from U.S. Census Bureau data to draw a sample from Harris County based on age, race/ethnicity, income, and health status. All participants in the survey were required to be age 18 years or older. The survey focused on the households' experience of disruptions that may have inhibited their access to basic needs (food, energy, water resources). Questions about the occurrence and magnitude of these obstacles, preparation and response behaviors, and the impact that disruptions had on the household were addressed, as well as information about their sociodemographic background. The purpose of the data was to highlight the trends in vulnerable population group experiences with infrastructure disruptions during a disaster event. As suggested by Lindell (2008) the degree to which sample means and proportions are representative of the study area population is less important than having enough demographic diversity to provide an adequate test of the relationships in the presented correlation analysis. A total of 1081 household samples were collected from 140 of the 145 zip codes in Harris County. According to power analysis, this is a sufficient number of responses to conduct inferential statistics that systematically examine associations within the survey data. Those with incomplete responses and those that had evacuated their households before Hurricane Harvey landed were eliminated from the analysis, narrowing the analyzed sample to 884 households.

Research Measures

Table 13 summarizes the variables used from the survey to measure each component of the framework. Food deserts were defined were households experienced food shortages. Food infrastructure is defined by the distance from the nearest grocery store and how many stores a household had to visit before obtaining sufficient supplies. The distance was specifically defined by a binary indicator representing whether a household lived in a food desert. The USDA defines a food desert as an area where the nearest grocery store is over a mile away and a majority of the population is low income and has little access to transportation (Ver Ploeg, Nulph, & Williams, 2011). The socio-demographic factors were drawn from themes commonly found in the social vulnerability literature identified by Rufat et al. (2015). Measures for the physical attributes, behaviors, and vulnerability were developed based on an in-depth literature review on disaster risks and vulnerabilities that are determined by the conceptual framework which informed the questions used in the survey. A 4-item Likert scale question captured households' perception of the risk of disruptions. Risk perception of infrastructure disruptions is included as an influencing attribute measure because it is driven by one's circumstances, surroundings, and past experiences (Lindell & Perry, 2012). From this explanation it is assumed that a household's perceived risk of infrastructure disruption is reflective of their trust and evaluation of their community's infrastructure systems and services. Another 4-item question dealt with residents' concern about potential consequences of the storm such as disruption of sup- plies, damage to public facilities, damage to houses or possessions, financial loss, psychological health, and inconvenience of the recovery process after the flood. Finally, a 4-item question dealt with how likely the respondents were to take preparation and protective measures to reduce the risk of flooding. The respondents used a 5-point Likert rating scale (0= Not at all to 4 =extremely) to evaluate each question in the survey. Any answers that had selections that indicated a lack of behavior was omitted, or turned into a "0", to prevent contradiction. Outliers were removed from much of the remaining numerical data used, such as days spent preparing. Multiple-choice questions that consisted of levels, such as from "[no hardship] at all" to "a great deal [of hardship]", were assigned numbers from 0 to 4. This allowed the data to be used in an empirical analysis. The low-income group included residents who selected their income to be $0-$25,000 as well as $50,000; low education included anybody who did not complete higher education.

STATISTICAL APPROACH

The data collected from the survey were analyzed using a combi- nation of bivariate and multivariate analysis to understand the under- lying characteristics of FEW vulnerable households. First, the nexus interactions were determined based on the response of households to the following question: "What were your primary needs for the following infrastructure services before and during the hurricane?" ANOVA testing and Structural equation models are formed to test the pathways proposed in the conceptual framework. The data and analysis focused on the differential preparation behaviors and FEW nexus disruptions' impacts on households in the context of a disaster event.

Bivariate Analysis – ANOVA 1-Way Testing

To observe the relationship between the FEW vulnerabilities and the disaster risk measures in the conceptual framework, the interquartile range of the dataset was determined according to the aggregated sum of the FEW hardship measures. The disaster risk variables measuring physical attributes, sociodemographic characteristics, preparedness behaviors, and disruptions were evaluated and compared by categorizing households as either low, medium, or high vulnerability according to the percentile range of their combined FEW vulnerability scores (the aggregated sum of FEW hardship measures). ANOVA one-way tests were used to compare the mean values of the disaster risk measures among the non-vulnerable and vulnerable households and examine if differences are statistically significant.

In order to evaluate pair means, a Tukey HSD post hoc test was conducted. Accordingly, structural equation models were developed using the disaster risk measures which were found to be statistically significant in households demonstrating higher FEW vulnerabilities according to the post hoc test analysis.

Structural Equation Modeling

The framework is then analyzed via exploratory structural equation modeling (SEM), with the Lavaan Package (Rosseel Y (2012) on R Studio software. SEM is beneficial because it allows for the creation of latent variables from existing data, and then uses logistical regression to compare the correlation between the latent variables and identifies significant pathways. The resulting coefficients indicated the significance of the indices and allowed for further interpretation. Lavaan is particularly useful in that it provides fit data to determine how well the framework functions. SEM is selected as a statistical tool because it can estimate multiple and interrelated dependence relationships simultaneously. This allows us to assess the significance and strength of a particular relationship in the context of the complete model. We want to see if the model as proposed in the discussion of the conceptual framework is validated by the empirical survey data that has been gathered by households and their experience with Hurricane Harvey. The overall objective of structural equation modeling is to establish that a model derived from theory has a close fit to the sample data in terms of the difference between the sample and model-predicted covariance matrices. To test the proposed relationships among the study variables as shown in Table 13, structural equation modeling (SEM) was developed using Maximum likelihood (ML) as an estimation method. For model evaluation purposes the following fit indices are used, and their thresholds are as follows: The Root means square error of approximation (RMSEA < 0.07), the Comparative Fit Index (CFI > 0.95) and the Tucker Lewis Index (TLI > 0.95). The RMSEA also takes the model complexity into account as it reflects the degree of freedom. RMSEA value smaller than 0.05 can be said to indicate a convergence fit to the analyzed data of the model while also indicating a fit close to good when it produces a value between 0.05 and 0.08.

Being an exploratory analysis, multiple models were fitted to test for the effect of disaster risk measures and sociodemographic characteristics on the associative pathways in the proposed conceptual frame- work. The first model is run without testing for the sociodemographic effects while the subsequent models are fitted with the measures as- sociated with zip code areas with high FEW vulnerabilities.

RESULTS

FEW Nexus Interactions During Hurricane and Flooding

Table 14 summarizes the key household-level nexus relationships based on the results from the household survey. For example, electricity was identified as a need for heating and preparing food and water and maintaining the livability of homes. Water and food needs were un-surprisingly cited for health and livability needs. Mapping these households FEW nexus needs highlights another significant sub- component of the nexus which is the health and well-being of house- holds. Ultimately, these systems provide the means for and support health and well-being.

Bivariate Analysis

Table 3 summarizes the underlying characteristics of FEW vulnerable households. The survey variable represents the measures used according to each of the four constructs of the proposed nexus-disasters framework,

Table 14: Household Nexus Relationships Based on Household Survey Responses: "What were your primary needs for the following infrastructure services before and during the hurricane?

Infrastructure	**Household-level nexus Interactions**
Energy	Indirect via transportation: getting food and water
	Food storage and preparation, boiling or heating water
	Livability of household (A/C, lighting, health treatments)
Water	Food preparation
	Health & Hygiene
	Drinking water
Food	Health needs
Infrastructure	**Household-level nexus Interactions**
Energy	Indirect via transportation: getting food and water
	Food storage and preparation, boiling or heating water
	Livability of household (A/C, lighting, health treatments)

Water	Food preparation
	Health & Hygiene
	Drinking water
Food	Health needs

Columns LQ1, LQ2, LQ3 represents households by the FEW vulnerability interquartile range, where the highest quartile represents households with greater vulnerability. For example, the average number of households in a FEMA Flood-zone located in areas of less vulnerability is 25.20 %, whereas 45.50 % of households in FEW vulnerable areas responded that they are in a FEMA flood zone. For complete test statistics, refer to Appendix B. These results helped to inform the variables used in the development of SEM models based on the High FEW-vulnerability being statistically significantly different from both medium and low vulnerability groups according to the ANOVA 1-way tests. Variables that were found to be statistically different from both groups have been marked with an asterisk. All variables were found to have different occurrences between at least one group. There were no statistically significant differences across the households concerning: having a power backup, using power for food, and using roads for food and water, and days preparing.

There was a statistically significant difference across households classified as low vulnerability, medium vulnerability, and high vulnerability as determined by one-way ANOVA concerning various dis- aster risk characteristics measured in the survey. A Tukey post hoc test revealed characteristics that were statistically significantly higher in High FEW vulnerable households compared to both low and medium vulnerability. Survey variables that were statistically significantly different between High FEW vulnerable households and Medium and Low vulnerability are indicated in the last column.

Households experiencing greater FEW-vulnerability were more likely to need FEW sources for health-related needs. This highlights another significant subcomponent of the nexus which is the health and well-being of households. Ultimately, these systems provide the means for and support health and well-being. The days spent preparing for the storm were not found to be statistically significantly different across highly vulnerable households and low vulnerable households. Similarly, there was no statistically significant difference among the engagement of households in preparedness actions. Households rating as more vulnerable to FEW disruptions on average, reported higher engagement in certain preparation activities where 12 % of the least vulnerable households did not engage in any preparation action at all, whereas only 5% of highly vulnerable households reported no engagement in preparation actions. An interesting finding from the ANOVA results was this discrepancy between extent or attempt to prepare and the household's perception of the importance of preparations. Households that were rated more vulnerable on average reported lower levels of importance towards preparation actions. Perhaps this represents the household's frustration with the effort and attempts to prepare but the lack of resources due to urban attributes. Vulnerable households do prepare, however, certain behaviors influenced by urban attributes inhibit the ability of the household to prepare sufficiently.

Most striking from the ANOVA analysis is the disparity in food and water supply at stores in the preparation phase of the disaster. 44 % of households rating as high vulnerability experienced supply shortages during their attempt to prepare, whereas only 1% of households rating very low in vulnerability experiencing shortages. FEW vulnerable households were much more likely to report high perceived risks to infrastructure disruptions, indicating there is not as much trust in the reliability and robustness of the infrastructure services and systems in the community of the household. Overall, vulnerable households were more likely to be close to hazardous areas such as in flood zones, close to drainage and stormwater infrastructure, and in areas of lower livability rating, as determined by the Houston SocioNeeds Index.

Table 15: Bivariate analysis - Underlying Characteristics of FEW Vulnerable Households

	Survey Variable	*Low FEW Vulnerability n = 93*	*Medium FEW Vulnerability n=530*	*High FEW Vulnerability n=261*	*ANOVA 1-way test result*
Physical Attributes	*% of households in a FEMA Flood-zone*	0.18	0.25	0.41	***
	% of households Neighborhood flooded	0.46	0.60	0.74	***
	Average Reported Flood duration	1.80	3.32	5.29	***
	Average Reported Road risk	2.07	2.44	2.83	***
	Average Reported Power risk	2.07	2.33	2.68	***
	Average Reported Water risk	1.48	1.90	2.48	***
	Average Reported Food risk	2.15	2.47	2.79	***
	Average Reported Fuel risk	2.03	2.28	2.77	***
	Average Reported Grocery store distance	2.35	3.04	3.47	***
	% of households experiencing Grocery store food/water shortage	0.01	0.09	0.44	***
	Flood proximity	0.42	0.50	0.57	**
	Index score	51.04	53.68	64.68	***
	Index rank	3.06	3.11	3.63	***
Disruption Duration	*Average Reported Food*	0.97	2.58	5.20	***
	Average Reported Roads	3.26	6.04	7.57	***
	Average Reported Water	0.19	0.37	1.27	***
	Average Reported Water boil notice	0.12	0.54	2.15	***
	Average Reported Power	0.27	0.59	2.04	***
Household Behaviors	*% of households with Power backup*	0.18	0.16	0.18	
	% of households reporting use of Power for food	0.71	0.74	0.77	
	% of households reporting use of Roads for food and water	0.80	0.84	0.84	
	% of households reporting use of Power for health	0.68	0.76	0.74	*
	% of households reporting use of Roads for health	0.18	0.20	0.35	***
	% of households reporting use of Water for food	0.68	0.76	0.76	*
	% of households reporting use of Water for health	0.84	0.88	0.94	*
	Average Days aware of hurricane	5.27	4.87	4.30	***
	Average Days of preparation	4.60	4.00	4.06	

	% of households reporting underestimating disruption impact	0.02	0.13	0.32	***
	% of households Did not prepare enough	0.11	0.51	0.86	***
	Average rating of Importance of preparation (out of 4)	3.02	2.74	2.65	***
	Took 3 or more preparation actions	0.62	0.67	0.63	
	Took no preparation action	0.12	0.07	0.05	
	Food prep	0.76	0.81	0.84	
	Water prep	0.78	0.83	0.87	
	Energy prep	0.83	0.86	0.87	
Sociodemographic Characteristics	*% of households with Prior disaster experience*	0.89	0.83	0.74	***
	Median Years lived in Harris County	30.68	24.06	24.26	***
	% of households with children Age; Under 2 years	0.25	0.43	0.57	**
	% of households with children Age; 11- 17 years	0.18	0.30	0.43	***
	% of households with Age;65+	0.62	0.49	0.23	***
	Median Income (1-7)	3.57	3.59	2.84	***
	% of households Minority	0.34	0.41	0.56	***
	Black	0.19	0.18	0.28	*
	Latino	0.07	0.14	0.16	**
	Other	0.05	0.05	0.09	
	White	0.67	0.60	0.40	***
	% of households College degree	0.65	0.64	0.45	***
	% of households Disability	0.11	0.21	0.23	***
	% of households Chronic Illness	0.25	0.34	0.30	*

** Significant codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1.

Structural Equation Model Results

SEM is selected as a statistical tool because it can estimate multiple and interrelated dependence relationships simultaneously. Results of the SEM model are presented and consistent with Journal Article Reporting Standards (JARS) (Hoyle & Isherwood, 2013) and (Schreiber et al., 2010). Using the hypothesized framework (Fig 11), the specified measures from the survey data (Table 13), and results from the above ANOVA testing, a base structural model consisting of 19 observed variables (Model 1, Fig 12) associated with 4 latent variables was developed. Five additional models were developed controlling for various sociodemographic groups, with the final model taking into account all sociodemographic groups. The results obtained from the SEM analysis show that the factor loadings for each of the items were significantly larger than their standard errors, and the associated t-statistics (critical ratio (C.R) values) exceeded ± 1.96 (at $p < 0.05$). A complete summary of the fit statistics and comparison with acceptable values is presented in Table 16. The latent factor loadings, regression, and covariance results of each model can be found in Tables B1–B3 in Appendix B.

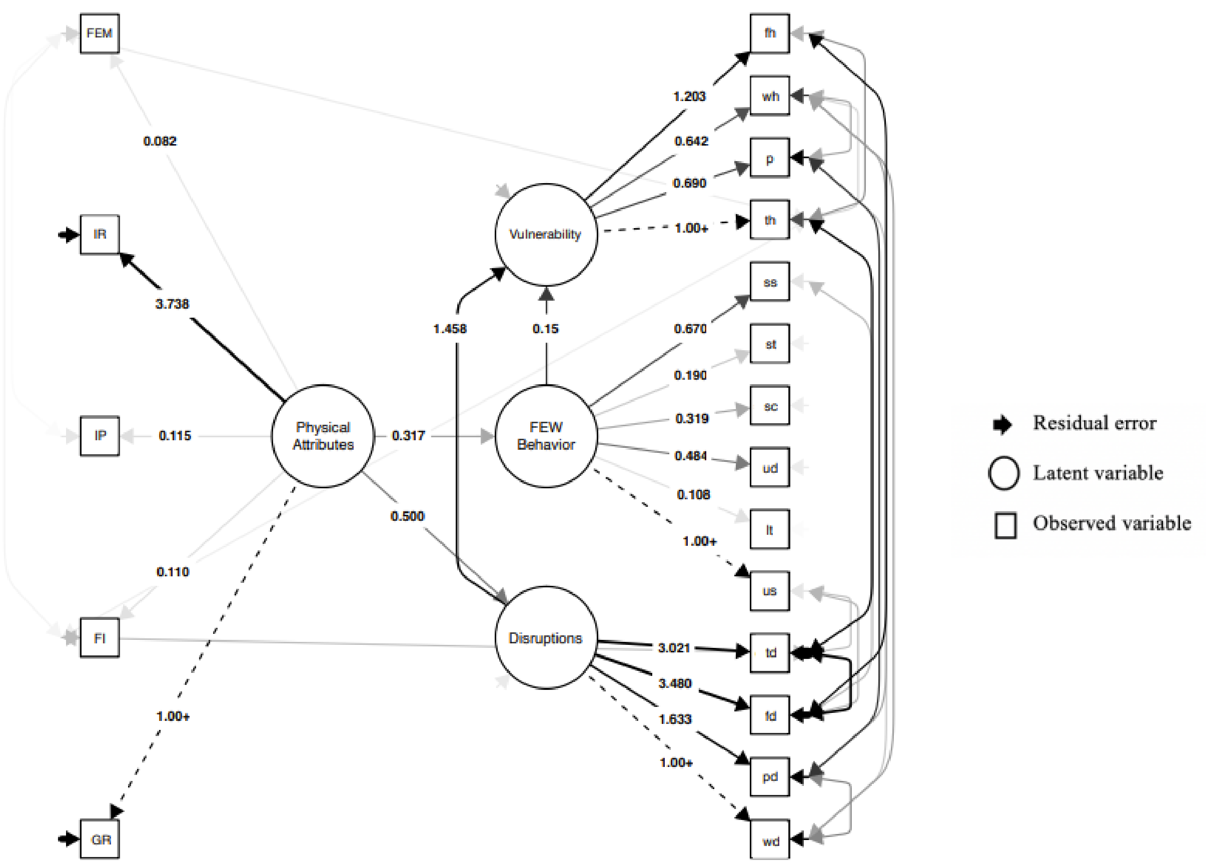


Figure 12: Model 1 pathway diagram; weighted lines indicate strong relationships, while shaded lines indicate weaker relationships. Dashed lines represent the factor loadings of the first indicators in each latent variable construct. The numerical values indicate the β values and factor loadings. FEM = FEMA flood zone; IR = Infrastructure failure risk; IP = Industrial plant proximity; Fl = Flood control infrastructure proximity; GR = distance to grocery store; fh = Food hardship; wh = water hardship; ph = power hardship; th = transportation hardship; ss = storage space; sc = supply costs; st = storage space; ud = underestimated disruptions; lt = lack

transportation; us = underestimated storm impact; td = transportation duration; fd = food duration; pd = power duration; wd = water duration.

Table 16: Summary of Model Performance Indices

Fit index	Model 1 (without vulnerable populations)	Model 2 (Control for Income, Education, Race)	Model 3 (Control for Disability)	Model 4 (Control for households with children)	Model 5 (Control for prior experience)	Model 6 (All variables)	Recommended Value*
RMSEA	0.000	0.020	0.000	0.001	0.007	0.020	<= 0.05
TLI	1.009	0.967	1.004	1.000	0.996	0.950	Approaches 1
CFI	1.000	0.973	1.000	1.000	0.997	0.960	>=0.95
P-value (Chi-square)	0.800	0.000	0.639	0.482	0.332	0.000	> 0.00

All the fit statistics were within the accepted fit ranges for all models tested (Table 16). It is apparent that the model performance is sacrificed slightly when accounting for vulnerable populations in the SEM. Most of the pathways between the exogenous variables and the endogenous variables are statistically significant at the 0.001 and 0.01 level of significance. A good fit indicates that the variance in the variance- covariance matrix is well represented by the models. A complete summary of the test results for each model, including the latent factor loadings, variances, covariances is included in Appendix Section B.

Model 1: Base Model Without Social Factors

The physical attributes of a household's community are moderately strong indicators of their ability to sufficiently prepare for a disaster ($\beta = 0.317$, $p = 0.000$). Similarly, the physical attributes of a house- hold's community are strongly indicative of the extent of disruptions experienced ($\beta = 0.500$, $p = 0.000$). These findings alone highlight the strong intersection of the pre-existing conditions of a community and its vulnerability at both a social and physical perspective. Ultimately, disruptions are more significant in determining FEW-vulnerability (β = 1.458, p = 0.000) compared to preparation behaviors (β = 0.717, p = 0.000), though it is still strongly associated and statistically significant; for every one-unit increase in a household's FEW-vulnerability, the likelihood that a household will not have proper access to resources, whether through knowledge, supply, and or money, will increase by 0.72.

Model 2 - Control For Income, Education, and Racial Minorities

Being of a racial minority is positively associated with lower levels of preparation behaviors (β = 0.220, p = 0.000). Income and education have a negative correlation (β = -0.02, p = 0.018; β = -0.02, p = 0.045), which signifies that decreasing household income and lower attainment of education are associated with poorer preparation behaviors. When adjusted for these variables, the behavior is still a significant indicator of FEW vulnerabilities, but compared to Model 1, the coefficient is reduced (β = 0.490, p = 0.025). The association be- tween FEW vulnerability and preparation behaviors is smaller after adjusting for income, race, and education level. The behavior remains statistically significantly associated with FEW-vulnerability, but the magnitude of the association is lower after the adjustment. The regression coefficient decreases by nearly 46 %. It can be concluded that the model supports the constructs and pathways proposed in the conceptual framework. The association between disruptions and FEW- vulnerability (β = 1.55, p = 0.025) also appears to have been impacted by the inclusion of these sociodemographic variables. The magnitude of association increased by 8.30 %, meaning that part of the association between FEW - vulnerability and Infrastructure Disruptions is explained by low income, low education attainment, and minority racial status.

Model 3 – Control for Age (Households With Young Children)

From the ANOVA testing, it was found that less vulnerable house- holds were more likely to have elderly residents while more vulnerable households were more likely to have children. Therefore, this model introduces households with children under 10 years old as a measure of a vulnerable population group during disasters. Households with children had a statistically significant yet mild association with prepared- ness ($\beta = 0.09$, $p = 0.000$). The association between physical attributes and preparedness remains statistically significant and the magnitude of the relationship is reduced only slightly. There is therefore a slight indication that the relationship between the two constructs is explained by households with children. The association between FEW vulnerability and preparedness behaviors is also explained by households with children.

Model 4 - Control For Disability

Model 4 tests for the effect of a household having a resident with a disability. Disability was selected based on the results of the ANOVA testing. When controlling for households with a disabled resident, all measures remain statistically significant. However, it appears that having a disability has a minor impact on the level of preparation ($\beta = 0.09$, $p = 0.001$), while its association with the outcome variable, FEW-vulnerability, is slightly greater ($\beta = 0.170$, $p = 0.11$).

Model 5 - Control For Prior Disaster Experience

Lastly, the prior experience was introduced to a fifth model to determine its role in a household's vulnerability to a FEW disruptions (Appendix B, Table 5). Overall, households having prior experience with a disaster were more likely to not face issues with preparing for a storm (β=-

0.23, p=0.001). Having prior experience in disaster situations was similarly associated with lower FEW vulnerability, as indicated by its inverse relationship ($\beta = -0.12$, $p = 0.000$).

Model 6 – Control for All Social Attributes

Table 17 presents a decomposition of the standardized direct, indirect, and total effects of each model construct and social attributes on household FEW-vulnerability, as well as the particular indirect effects modeled through various pathways and the total effects of each of the model's mediating variables. A sixth model was constructed and fitted with all of the social variables to determine the total relative weight each variable has in influencing a household's vulnerability to food, energy, and water infrastructure disruptions during a hurricane event. In the 6th model (Table 17), urban attributes, household preparation behaviors, and infrastructure disruptions had a significant direct (1.634) effect on household FEW-vulnerability, while indirect effects were minimal (0.011). From Model 6, it can be inferred that the probability of a household experiencing greater vulnerability to the combined effects of food, energy, and water infrastructure disruptions increased by 162.4 % of a standard deviation for every one standard deviation increase in the duration of infrastructure disruptions and increase in poor preparation behavior. Of the mediating variables tested in the model, the duration of infrastructure disruption experienced (1.622) had the largest total effect on household vulnerability, followed by preparation behaviors (0.404), Race/Ethnicity (0.245), and prior disaster experience (-0.230). Income and educational attainment level of a household appears to have a negative but minimal effect on a household's vulnerability to food, energy, and water infrastructure disruptions (-0.039; -0.049).

Table 17: Total, direct, and indirect standardized effects of urban attributes, preparation behaviors, infrastructure disruptions, and social factors on FEW Vulnerability.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Total (All attributes to FEW)	1.535	1.557	1.570	1.606	1.549	1.634
Total Indirect (All attributes to FEW)	0.012	0.011	0.012	0.012	0.012	0.011
Total Direct (All attributes to FEW)	1.547	1.568	1.582	1.618	1.561	1.645
Specific Indirect Effects						
Urban to disruption to FEW	0.213	0.216	0.215	0.222	0.215	0.227
Urban to behavior to FEW	0.057	0.040	0.055	0.050	0.051	0.032
Prior to behavior to FEW	–	–	–	–	−0.075	−0.030
Race to behavior to FEW	–	0.043	–	–	–	0.024
Income behavior to FEW	–	−0.008	–	–	–	−0.006
Education behavior to FEW	–	−0.007	–	–	–	−0.004
Age behavior to FEW	–	–	–	0.051	–	0.026
Disability behavior to FEW	–	–	0.062	–	–	0.030
Total Effects						
Urban Attributes	0.224	0.221	0.222	0.223	0.686	0.220
Disruptions	1.524	1.546	1.558	1.595	1.537	1.622
Behavior	0.671	0.488	0.655	0.596	0.601	0.404
Experience	–	–	–	–	−0.354	−0.230
Race/Ethnicity	–	0.303	–	–	–	0.245
Income	–	−0.042	–	–	–	−0.039
Education	–	−0.061	–	–	–	−0.049
Age	–	–	–	0.214	–	0.143
Disability	–	–	0.260	–	–	0.206

*All values significant at $p < 0.05$.

DISCUSSION

The empirical data and statistical analysis applied in this study re- veal that physical attributes, the extent of disruptions, household preparation behaviors, and sociodemographic characteristics each con- tribute to a household’s vulnerability to FEW disruptions. This relays the notion that pre-existing conditions of communities in which households live have a significant role in determining their risk and vulnerability to disaster impacts. Consequently, heightened vulnerability corresponds to low levels of resilience: households will face more challenges in recovering from impacts and withstanding future hazardous events.

The use of ANOVA one-way testing allowed for the identification of disaster risk measures that are significantly different across different thresholds of household vulnerability, in other words, which disaster risk measures are more prevalent in households experiencing greater FEW-vulnerability? Structural equation models were used to measure the magnitude of the proposed pathways of the Nexus-Disaster frame- work based on the feedback of the ANOVA results. In summary, certain measures of disaster risk were found to be more prevalent in households experiencing significant levels of FEW vulnerability, whereas the structural equation models supported the theorized pathways between the disaster risk and infrastructure nexus constructs of the proposed conceptual model guiding this research study. The following discussion highlights significant findings and their implications with respect to the existing disaster literature.

Pre-Disaster Conditions Influence Household Vulnerability to FEW Disruptions

Urban attributes influence household vulnerability by increasing the duration of disruptions and diminishing the ability for disaster preparations of each household. Based on the results, preparation behaviors, duration of infrastructure disruptions, and the urban attributes of communities collectively contribute to the FEW- vulnerability of households during a hurricane.

Vulnerable households were more likely to reside in close proximity to flood control infrastructures such as bayous or dams, FEMA designated flood zones and areas of low social, health, and community ser- vices as defined by the Houston SocioNeeds Index. Interestingly, vulnerable households were more likely to report higher perceived risk to infrastructure system failures. This may indicate their experience of disruptions in FEW infrastructure systems overall. They also lived further from the grocery stores and experienced supply shortages at grocery stores during storm preparation.

The bivariate analysis conducted using ANOVA one-way tests con- firms that preparation behaviors are significant indicators of household vulnerability to FEW disruptions during disasters. The duration of preparation and extent of preparedness actions taken by households varied only slightly across the FEW infrastructure vulnerability thresholds and did not appear to be significant indicators of household vulnerability to infrastructure disruptions. On the other hand, preparation behaviors appear to play a significant role in determining the vulnerability of households to food, energy, and water disruptions, however, the duration of preparation and the number of preparation actions households took do not appear to be strong indicators of vulnerability. According to the ANOVA one-way tests, the average preparation days are not statistically significantly different across house- holds scoring low in vulnerability and high. Similarly, households regardless of vulnerability status appear to have similar behavior and demand with regards to the need for water, energy, and food resources immediately before, during, and after the storm. However, it did appear that households scoring higher in vulnerability were more likely to report needing power, transportation, and water for health purposes compared to low vulnerability households. Fothergill and Peek (2004) noted similar findings in their research investigating preparedness behaviors before Hurricane Andrew in 1992. They found the type of preparedness activities and their timing were consistent across different income groups.

This finding demonstrates the need for infrastructure systems to address the needs of vulnerable population communities to ensure better livability before and after disruptive events like hurricanes. In terms of policy development, this translates to building and redesigning city infrastructure (such as grocery stores) in ways that cater to population needs (i.e. human-centric planning) and for city planners to address and social inequities that already exist in communities.

Prior Disaster Experience is a Significant Indicator of Preparation Behaviors and Vulnerability

Not being able to prepare enough due to shortages of supplies at grocery stores was positively correlated to the reported duration of food infrastructure disruptions. Physical attributes ($\beta = 0.290$, $p = 0.000$) and prior experience ($\beta = -0.120$, $p = 0.000$) with disasters were found to be the most significant indicators of poor preparation behavior. While sociodemographic characteristics of households were shown to have a statistically significant association in the pathways leading to FEW-vulnerability and with FEW-vulnerability itself, prior disaster experience was found to be a stronger indicator of FEW-vulnerability and preparation behaviors overall. This means that holding sociodemographic characteristics constant, households with prior disaster experience are less likely to be vulnerable to FEW disruptions. This finding is in agreement with past research which has shown that direct experience of a disaster can be a strong motivator of preparedness (Becker, Paton, Johnston, Ronan, & McClure, 2017). Several preparedness theories and approaches suggest that prior experience of earthquakes and other disasters influences the preparedness process (Rogers, 1983; Mulilis et al., 2003; Lindell & Perry, 2012).

Social Vulnerability Explains the Extent of Preparedness Actions and Influences FEW Vulnerability

Through the bivariate and multivariate analysis, household FEW vulnerabilities were found to be statistically significantly associated with vulnerable population groups, namely: less-educated, racial minorities, lower-income households, households with young children, and households with disabled and limited mobility members. In terms of preparation behaviors, vulnerable households were less likely to have power backups and had greater dependencies on FEW resources for health-related purposes. Related to preparation behaviors, vulnerable households also had a greater tendency to underestimate the im- pact of the disaster and expressed having more barriers to storm preparation. They were more likely to report “not being prepared enough,” due to either cost of supplies at stores, supply shortages at the stores, underestimating storm impact, lack of transportation to stores, or a combination of these factors. This finding provides a critical perspective to previous research findings which have concluded that vulnerable populations are less likely to prepare for disasters (Ballen, 2009). Some research has found residents of low social and economic status to be less prepared than other residents for disasters. This study shows that level of preparation has more to do with the existing services and access to services and supplies (urban attributes) before the storm. Being less prepared has less to do with the duration of preparation. Preparation depends on costs, availability of supplies at stores, access to reliable transportation, access to adequate storage. This is also supported by research conducted by Gladwin and Peacock (1997), in which the time between beginning preparation and the onset of the hurricane did not vary significantly by socioeconomic status, in this case, measured by income.

The findings are aligned with the outcomes of other research showing that certain demographic characteristics determine necessities to prepare and associated with an increase in the likelihood of preparedness for an example, having dependent members in the home (Ablah et al., 2009; Hoffmann and Muttarak, 2017) and having children (Basolo et al., 2009; Eisenman et al., 2009). The outcomes of prior studies provide context to the finding that vulnerable households were more likely to report needing or using FEW resources for health-related purposes.

Infrastructure Disruptions and Hardship Experienced are Interconnected

Of all of the nexus system interactions, water and power appear to have the strongest interdependency. The duration of water disruption experienced by households and power outages were statistically significant ($\beta = 0.460$, $p = 0.005$), as were the hardships experienced for both:

the reported hardship experienced due power outages was positively correlated to experiencing water hardships ($\beta = 0.290$, $p = 0.000$). These positive and statistically significant correlations provide empirical evidence related to the strong linkage of water and power in the context of hurricanes and flooding disasters. Similarly, we observe that increasing the duration of water outages leads to an in- crease in power hardship ($\beta = 0.200$, $p = 0.007$), whereas the relationship between power outage duration and water hardship is slightly stronger ($\beta = 0.320$, $p = 0.008$). Interestingly, there is a negative relationship between transportation hardship and food hardship ($\beta = -0.320$ $p = 0.001$). It appears that food hardship was greatly determined by pre-disaster conditions of grocery stores: stores already facing shortages prior to the storm were perhaps less likely to have supplies during and immediately after the storm, therefore increasing the extent of hardship and duration faced by households (supply shortage $\sim\sim$ food duration, $\beta = .250$, $p = 0.000$). Transportation hardship appears to be independent of FEW infrastructure systems considered in this study.

Households who had water shutoffs were especially vulnerable to hardship in all areas. The deficiency of clean water may have made food preparation more difficult: some food needs to be washed before consumption or needs to be boiled. One cause of water hardship could be water facilities relying on the output from power sources; a power outage may have affected water utilities nearby and caused dual disruption. Most pumps and wastewater treatment plants rely on the power grid to function and may not all have a backup generator (Miles et al., 2015). A power outage could have also made it difficult to heat water in a household that uses only electric appliances. This made hygiene, laundry, and food preparation and sanitation much more difficult. Plus, if a household was unable to boil their water when they have a boil notice, their access to clean water was limited.

Households that experienced greater FEW vulnerability experienced longer disruptions across all infrastructure services compared to households that reported none to minimal hardship due to the respective service. For example, Table 15 shows that on average, house- holds in the upper percentile range of FEW vulnerability experienced 7.57 days of disruptions to transportation services, while households in the lower percentile range of FEW vulnerability experienced on average of 3.26 days of disrupted services. This relationship is also apparent in the results of the structural equation models, where the latent variable, infrastructure disruptions, is positively associated with the latent variable, FEW vulnerability. The structural equation model also justifies the proposed relationship between urban attributes and disruptions. The assumption was that urban attributes measure the quality of services and the living environment of the households. The model proposed that the infrastructure disruptions along with the duration of the disruption are influenced by the urban or physical attributes of a household's community or surrounding environment. Across each model analyzed, this proposed pathway was supported, being positively correlated.

STUDY LIMITATIONS

To the best of the authors' knowledge, this study was the first at- tempt to assess FEW system interactions and impact at the household level in the context of a natural disaster. The analysis can be improved upon by integrating other data types into the modeling and analysis, such as measures for physical attributes of cities that might not be accurately depicted by households due to lack of knowledge or concern. Despite the limitations presented, this study was able to successfully identify the foundation of a causal model using SEM. The results show that there are additional variables that may influence vulnerability. There are other factors of disaster risk which were not explored in this paper, particularly social capital and information distribution, which may be significant indicators of FEW vulnerability. It is apparent that there are additional factors that influence a household's resilience to infrastructure disruptions and impact brought on by disasters. The results hint at the idea that vulnerability is not a factor of disruptions alone, but a result of complex interactions between a household and its access to certain services, proximity to hazardous areas, and access to food and water services. While the bivariate analysis shows that more vulnerable households are more likely to display more vulnerable characteristics, in the presented SEM model, sociodemographic characteristics do not appear to have as significant of a role as anticipated. Preparation actions were found to have a significant direct role in determining FEW-vulnerability. Further investigation is needed to understand which factors determined why certain households were not able to prepare sufficiently for the hurricane event.

CONCLUDING REMARKS

The results of the model specified the effects of infrastructure disruptions on households' access and use of FEW resources and informed about the household-level attributes and behaviors that shape demand and access to FEW resources in the context of natural hazards. As a result, the following gaps in our understanding of FEW nexus system interactions and vulnerabilities at the household level were addressed: (1) urban attributes and disaster characteristics influence the sensitivity of vulnerable populations to FEW system disruptions, (2) the nature and extent interdependencies among urban food, energy, and water systems influence households' demand and access to these critical resources during extreme weather events, (3) the cascading effects of disruptions in one system of FEW nexus on households' demand and access to re- sources from other systems, (4) the preparation behaviors that influence the extent of impact experience by FEW disruptions.

Resiliency and disaster recovery planning for natural hazards entails navigating the complex interactions among the social and infrastructure systems that support our cities. Many overlapping factors are at play that collectively contribute to household vulnerability during disasters, as evident from the results and findings of the structural equation models. Most of these challenges can be mitigated by addressing in- equities in infrastructure systems and social inequities. Given the future projections of more intense and frequent storms tied to climate change (Risser & Wehner, 2017), it is becoming more necessary to recognize infrastructure and system interdependencies as a component of disaster preparedness and resiliency. This study is part of an overall effort to better understand the effects that disasters have on people and com- munities as they relate to the built environment and social fabric of cities. Through the descriptive analysis and the development of SEM models based on the proposed FEW-Disaster framework, our empirical understanding of the nexus between FEW infrastructure systems and households during disasters has been refined. The urban attributes of communities play a significant role in the preparedness of households before the storm, which has significant implications on the overall vulnerability of households to FEW disruptions. Consequently, vulnerable population groups, particularly racial minorities, low-income households, households with young children, and households with a disabled resident(s) are at greater risk of disaster impacts due to FEW disruptions. The extent of preparation measured by the reported days of disruption and extent of preparation actions taken by households do not appear to mitigate vulnerabilities.

Findings from this research may be used to create a model for stakeholders and government leaders to simulate the effects of future disasters. By making disasters more predictable, funds can be allocated more efficiently, and policies can better prioritize protection for com- munities most affected by disasters. Fourth, the information collected in this study will provide a basis for developing a defensible empirical agent-based model (in future studies) in order to provide a robust analytical tool for decision-making and planning. This information is essential in identifying vulnerabilities and devising resilience- enhancing strategies to better cope with FEW nexus disruptions in disasters. This understanding will inform decision-makers and FEW resource providers to better prepare and respond to disruptions to minimize the impacts on households. This information is expected to inform plans that guide urban developments as well as resilience improvement in- vestments to minimize the impacts caused by FEW disruptions on vulnerable populations.

ACKNOWLEDGMENTS

The authors would like to acknowledge the funding support from the National Science Foundation under grant number 1846069, NSF Sustainability Research Network (SRN) Cooperative Agreement1444758, and an Institutional Grant (NA18OAR4170088) of the Texas Sea Grant College Program from the National Sea Grant Office, National Oceanic and Atmospheric Administration, U.S. Department of Commerce. Any opinions, findings, conclusion, or re- commendations expressed in this research are those of the authors and do not necessarily reflect the view of the funding agencies

CHAPTER V: STUDY 4 - DISSECTING HETEROGENEOUS PATHWAYS TO DISPARATE HOUSEHOLD-LEVEL IMPACTS DUE TO INFRASTRUCTURE SERVICE DISRUPTIONS

OVERVIEW

The objective of this study is to empirically and systematically assess the combination of inherent susceptibility factors, protective actions, and factors of hazard exposure that influence a household's level of hardship experienced due to disruptions in critical infrastructure services during disasters. Classification and regression tree (CART) decision tree models and survey data from three major hurricane events were used to: (1) identify the pathways leading to impact(s) due to service disruptions and explore the differences in pathways across vulnerable population groups; and (2) identify the points of intervention to mitigate well-being impacts in households due to disruptions in water, energy, food, and road transportation services. The results reveal how the associative pathways between these factors change between socioeconomic and demographic groups in the impacted community and for different infrastructure service system types. The findings suggest that not all vulnerable households experienced high hardship outcomes despite prolonged outages. Finally, the hardship pathways suggest recommendations for improving resilience in infrastructure systems in a more equitable manner. The findings can be used by emergency and infrastructure managers and operators to better prioritize resource allocation for hazard mitigation investments and restorations. Accordingly, this study contributes to the theory of human-centric infrastructure resilience.

INTRODUCTION

The objective of this study is to identify the combination of factors related to inherent susceptibility, risk exposure, and protective actions and their resultant hardship outcomes in households affected by infrastructure service disruptions during disasters. By identifying the combination of these factors, or *pathways*, this study informs more human-centric resilience strategies in infrastructure systems. Standard infrastructure resilience approaches focus on the understanding performance and functionality loss of systems to predict service disruptions (Batouli & Mostafavi, 2018; Cassottana, Shen, & Tang, 2019; Cimellaro, Reinhorn, & Bruneau, 2010; Poulin & Kane, 2021; Rasoulkhani & Mostafavi, 2018; X. Zhao, Cai, Chen, Gong, & Feng, 2016; Y. Zhao, Li, Zhang, & Wang, 2016). The prioritization is in terms of how critical certain functional components are to the entire network (Clark, Seager, & Chester, 2018). These approaches for infrastructure resilience and prioritization ignore the key societal pacts on households caused by failures and disruptions. Consequently, the application of such approaches would lead to restorations and infrastructure changes that do not improve or reduce the social impacts of infrastructure services in a socially equitable way (Coleman, Esmalian, & Mostafavi, 2020a; J. Dargin, Berk, & Mostafavi, 2020; J. S. Dargin & Mostafavi, 2020; Esmalian, Dong, Coleman, & Mostafavi, 2021; Kane & Vajjhala, 2020; Podesta, Coleman, Esmalian, Yuan, & Mostafavi, 2021).

There is growing research and evidence that infrastructure service disruptions affects households differently (Chang, 2016; J. Dargin et al., 2020; J. S. Dargin, Fan, & Mostafavi, 2021; Esmalian, Dong, Coleman, et al., 2021; Esmalian, Dong, & Mostafavi, 2021; Fan et al., 2020; Hallegatte, Rentschler, & Rozenberg, 2019; Mitsova et al., 2021). Recent literature has pointed towards the differences in well-being and hardship impacts households experience (J. Dargin et al., 2020; J. S. Dargin & Mostafavi, 2020). Several factors have been identified as contributing to variations in the impacts of service disruptions for subpopulations (J. Dargin et al., 2020; Esmalian, Dong, Coleman, et al., 2021). Despite this growing literature, our understanding of the pathways—the combination of factors that lead to these differential impacts—remains limited. Also, calls for more human-centered infrastructure planning and resilience have been made by researchers in disaster science ang engineering, among other disciplines. ((NSF), 2019, 2020; Chester et al., 2021; Council, 2014; Peters & Broersma, 2013; Schooling, Enzer, & Didem, 2020)). However, the theory of human-centric infrastructure system resilience at the household level is still in its nascency and the role of infrastructure system resilience at the household level has only recently received attention (Coleman, Esmalian, & Mostafavi, 2020b; J. S. Dargin & Mostafavi, 2020). The inadequate empirical information about the underlying mechanisms and extent of households' susceptibility to infrastructure service disruption has led to the weak consideration of the human-centric aspect in assessing the disparate societal impacts of infrastructure disruptions (Mostafavi & Ganapati, 2021).

An important step in advancing the theory for human-centric infrastructure is to identify the pathways composed of factors related to inherent susceptibility, protective actions, and risk exposure leading to disparate hardship outcomes, due to service disruptions, in households. These empirical insights and the identification of pathways offer important contributions to the development of the human-centric infrastructure resilience theory that attempts to explain human interaction with infrastructure systems during disasters and the disparate impacts experienced by households. The pathways reveal how the combination of factors yields different hardship impacts across different sub-populations and infrastructure systems. The pathways can help determine appropriate infrastructure- or household-level intervention gradients to collectively reduce the hardship impacts of service disruptions.

To address this knowledge gap, the objectives of this study are (1) to identify the pathways leading to impact(s) due to different service disruptions and to explore the differences in pathways across vulnerable population groups; and (2) to identify the points of intervention to mitigate well-being impacts in households due to service disruptions in water, energy, food, and road transportation services. Between 2017 and 2018, the Gulf and East Coast regions of the United States experienced a record-breaking hurricane season.

Data on household-level inherent susceptibility factors, protective actions, and exposure to critical infrastructure service disruptions of shelter-in-place households during three major hurricane events were collected. Classification and regression tree (CART) analysis was applied to identify pathways that distinguish households that experience high levels of hardship due to service disruptions during disasters. Using CART results to identify the differential pathways of hardship impacts in affected subpopulation groups, the following critical questions about household-infrastructure resilience were answered: (RQ1) To what extent do the pathways to hardship impacts differ across different income and racial groups?; (RQ2) To what extent do the impacts of pathways to hardship vary across infrastructure services?; and (RQ3) What infrastructure- and household-level intervention strategies could collectively reduce the disparate impacts of infrastructure service disruptions for vulnerable populations?

METHODOLOGY

Conceptual Framework

The empirical analysis implemented was guided by a conceptual framework (Fig. 13) that builds upon previous studies which have established that: (1) hardship disparities in service disruptions during disasters are associated strongly with vulnerable population groups (J. S. Dargin & Mostafavi, 2020; Esmalian, Dong, Coleman, et al., 2021); (2) there is a bi-directional relationship between household protective actions and the built environment in determining hardship outcomes in households during service disruptions (J. Dargin et al., 2020); and (3) disparities in access to information surrounding service disruptions as a form of a protective action during disasters (J. S. Dargin et al., 2021; Fan et al., 2020). Based on the findings of these earlier studies, hardship mitigation infrastructure improvements for households sheltering in place during disasters can be approached from three primary dimensions: **exposure reduction**, **enabling protective actions**, and **understanding inherent susceptibilities** to service disruptions. The combination of protective actions and inherent susceptibility factors determine different levels of household hardship outcomes. The factors selected in this study are explained in this section and are further summarized in Table 18 and Table 19. This framework allows for an exploratory analysis of the pre-existing conditions of households that can move stakeholders closer to answering the question of why households experience more significant impacts despite facing the same storm and same service outages.

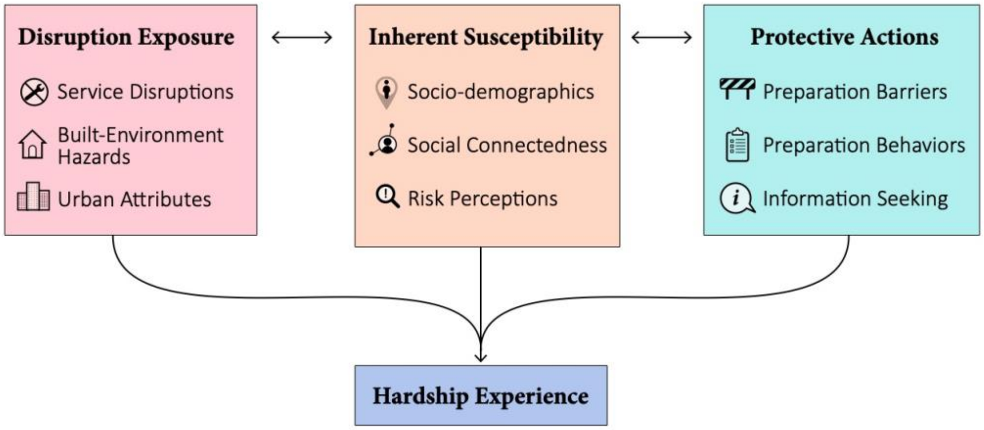


Figure 13: Conceptual framework, Study 4

Disruption Exposure Reduction

In the framework, risk exposure is measured by three components (1) service disruption duration and (2) residential characteristics and, (3) community infrastructure hazards. The community infrastructure hazards highlighted in this study are those relevant to food, electricity, water, and road infrastructure systems and their role in pre- and post-disaster situations. Community infrastructure hazards include food deserts measured as the proximity to the nearest grocery store, FEMA-designated flood zones, and proximity to stormwater infrastructure. These attributes were selected because of their roles in social equity and stormwater mitigation, which are significant in the face of hurricanes (J. Dargin et al., 2020). Furthermore, these variables influence the preparation (Baker, 2011), adjustment (Lindell & Hwang, 2008), and exposure (Koks, Jongman, Husby, & Botzen, 2015) of households to service disruptions.

Protective Actions

In the context of infrastructure disruptions, two types of protective actions important for households sheltering in place during disasters: (1) preparation and (2) information-seeking behaviors and the ubiquity of disaster communications regarding the extent of outage and updates on service recovery (Lindell & Hwang, 2008). A household's decisions related to protective actions are not only influenced by its attributes, such as sociodemographic characteristics, but they are also highly influenced by perceived risk from the hazard (Lindell & Hwang, 2008), information-seeking process (Morss, Mulder, Lazo, & Demuth, 2016), and their social network's influence (Haer, 2016; Kashani, Movahedi, & Morshedi, 2018). Preparation behaviors are significant predictors of household vulnerability to disruption in water, energy, and food infrastructures systems during disasters (J. Dargin et al., 2020). Differences in information-seeking behaviors prior to and during infrastructure disruptions can influence a household's situational awareness during storms and their ability to partake in appropriate protective actions (J. Dargin et al., 2020). Longer length of forewarning, increased perception of preparedness, and confidence in the households' capabilities correlated with lower levels of susceptibility to infrastructure service disruptions (Coleman et al., 2020a). All these factors of protective actions are explored in the analysis of this paper.

Inherent Susceptibility

Households intrinsically have varying levels of tolerance to cope with disruptions (Esmalian, Dong, & Mostafavi, 2021). Susceptibility to infrastructure systems disruptions is determined by social and physical characteristics of a community (Jeong & Yoon, 2018) (McEntire, 2011; Yoon, 2012). Factors influencing inherent susceptibility in this study are dominated by (1) sociodemographic characteristics, (2) perceptions of hazard risks, and (3) social connectedness or social capital.

Sociodemographic Characteristics

Sociodemographic characteristics refer to attributes of vulnerable groups who are often disadvantaged in the preparation for, response to, and recovery from disaster events (Coleman et al., 2020b). These groups include the elderly, households with children, low-income groups, ethnic and racial minorities, and people with chronic illness or disabilities.

Risk Perceptions

Risk perceptions are shaped by: (1) forewarning (the length of time in advance of the event that households first learn of an impending event), (2) the point in time that households start taking preparation actions, (3) information households received about the disruptions, and (4) the household's expectation of the duration of the disruptions. These variables can influence tolerance by affecting perception (Morss et al., 2016), protective actions (Lindell, Arlikatti, & Prater, 2009), and responses (Lindell & Hwang, 2008) to service disruptions.

Social Connectedness

Households with friends and family members on whom they can rely during the disaster can better cope with disruptions. Longevity in a community can be an indicator of social capital and community connectedness By the same token, the strength of social networks significantly contributes to risk perceptions (Brown, Daigneault, Tjernström, & Zou, 2018; Jones et al., 2013; Kosec & Mo, 2017; Liebenehm, 2018) and can mitigate the negative impacts of natural disasters on aspirations as related to well-being (Kosec & Mo, 2017).

Infrastructure Disruption Hardship

The extent of hardship is used as an indicator for examining the nature of experience related to a service disruption. A household's hardship experience is influenced by factors such the socioeconomic characteristics, preparedness, and access to resources (protective actions) (J. Dargin et al., 2020).

STUDY CONTEXT

The analysis in this study was performed based on a sample survey of 1,575 sheltering-in-place households impacted by three separate hurricane events on the Gulf and East Coasts between 2017 and 2018. Households were surveyed regarding their hardship experiences due to disruptions in water, electricity, road transportation, and access to food, in addition to different variables associated with their inherent susceptibility, protective actions, and specific hazard risks.

Three household surveys were deployed in the aftermath of Hurricanes Harvey (902 households), Florence (127 households), and Michael (546 households) to collect relevant service disruption data. Hurricane Harvey was a category 4 hurricane (highest wind speed 130 mph), which made landfall at Harris County, Texas, in August 2017. Harvey caused catastrophic flooding in Houston and caused severe disruptions in infrastructure services. Harvey was formed over the Atlantic Ocean on August 17, 2017, and made landfall August 25, 2017, a forewarning time of roughly eight days. Hurricane Florence was a category 4 hurricane with highest wind speed of 150 mph, making landfall and causing severe damage in the Carolinas in September 2018. This event caused flooding and was the wettest tropical cyclone of record in the Carolinas. Hurricane Florence was formed on August 31, 2018, fourteen made landfall at the Carolina coastal areas around September 13, a forewarning time of roughly fourteen days. Hurricane

Michael, which was a category 5 hurricane (highest wind speed of 160 mph), affected the Florida Panhandle in October 2018; it was one of the most severe wind events occurring in the United States. Hurricane Michael was formed on October 7, 2018, and made landfall on October 10, 2018, in Florida. Owing to its rapid movement, the hurricane allowed a forewarning time of around three days. These events, with Hurricane Harvey as a major flooding hurricane, Michael as an event with severe winds, and Florence with a combination of wind and flooding, were used to explore households' experience with infrastructure disruptions.

Survey Implementation

An online survey via Qualtrics was developed and conducted to empirically examine the factors affecting household hardship experiences due to service disruptions in the aftermath of Hurricane Harvey, Hurricane Florence, and Hurricane Michael. The survey was designed and deployed in close collaboration with the Texas A&M Public Policy Research Institute. The representative sample was provided by Qualtrics, a survey company that matches respondent panels with demographic quotas. Quotas created from the US Census Bureau data were provided to draw a representative sample from the region based on age, race/ethnicity, and gender. Data were primarily collected from households sheltering in place. The rationale for this selection was that, for the people who evacuated to shelters or other places, the relevance of infrastructure service disruptions became of secondary importance since they have already moved from shelter (the primary place in which infrastructure services are utilized). The focus of this study was to examine the impacts of infrastructure service disruptions on households; thus, coastal areas with evacuation orders were not included in the samples.

Data

The dependent variable, *Household hardship experience* (Table 1), is an indicator of the impact on well-being of infrastructure service disruptions measured by an ordered-categorical scale of low, moderate, and high. The independent variables (Table 2) used in the analysis were further classified according to the elements of the conceptual framework. Because types of households, based on sociodemographic classification, may have different paths to hardship, the data was stratified into 24 subsets according to (1) households that experienced one or more days of disruptions in an infrastructure service, and (2) by income and ethnic group (Fig. 14). The data were analyzed first, and then separately by each data subset to identify differences in hardship pathways according to income, ethnicity, and service disruption type.

The data for Hurricane Harvey were collected from Harris County (population of around 4.65 million). The number of responders for each focus area was designed to be proportional to the population of each ZIP code. Those who evacuated their homes and flooded households were removed from the analysis. The Hurricane Harvey survey numbered 1,008 complete responses, from which 902 were used for creating the models after removing surveys of households which evacuated. Household data for Hurricane Florence were collected from affected counties in North Carolina, with a combined population of 1 million. A total sample of 573 responses was collected, with 546 used for analysis. The largest number of responses for Hurricane Michael was collected from the residents of Florida. The impacts of infrastructure service disruptions extended to residents of Georgia and Alabama; thus, we enlarged our sample to include those households as well. This survey contained 706 responses, from which 127 responses were drawn for developing the models. A total of 1,575 responses were used from the original surveys after removing households that did not experience any service disruptions and did not evacuate their household at any point before or during the hurricane event. According to power analysis, this is enough responses to generate inferential statistics that systematically examine associations in the resulting data**.** Survey questions focused on vulnerability, protective actions, and risk exposure factors at the household level: expectations from infrastructure services, prior experience with disasters, risk perceptions, preparedness, infrastructure service interruptions, adaptation strategy and substitutes, and well-being impacts. Factors that may be relevant to the way that the respondent experiences and responds to hazard event, include gender, race/ethnicity, age, socioeconomic status, number of dependents, employment, disability, and home-owner status.

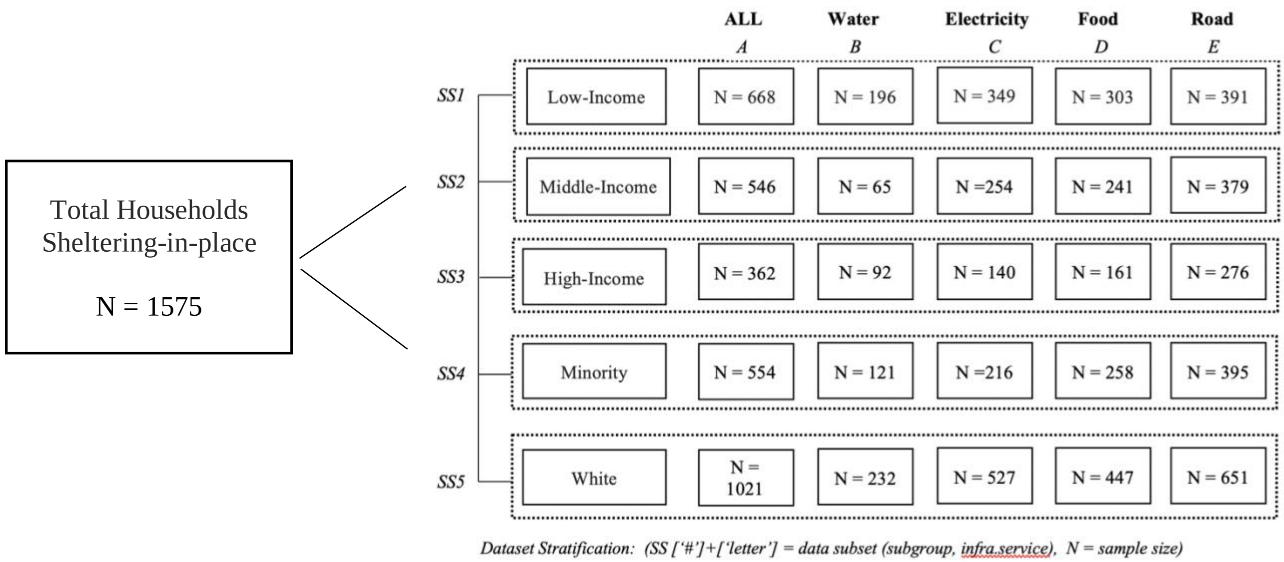


Figure 14: Visual representation of the data sample stratification process. 24 total samples were stratified by subgroup population and households affected by service disruption from the original sample (N=1,575 sheltering-in-place households). SS is short for 'subset, and letters are used to categorize the subsets by infrastructure service subsets (i.e., SS1-A refers to all low-income households from all datasets).

Table 18: Independent variables of household-infrastructure resilience used in CART models.

	Dependent Variable(s)	Variable	Metric	Survey Question
Infrastructure Service Disruption(s)	Water Power Food Roads/ transportation	Household Hardship Experience	Low Moderate High	To what extent did you and your household experience hardship due to outages and disruptions to the following infrastructure services during the hurricane event?

Table 19: Dependent variables used in CART models

Hardship mitigation approach	Variable Name	Measurement	Survey Question
Hazard Exposure	Neighborhood flooded	Number of days of flooding reported	For how many days was flood water in your neighborhood?
	Disruption duration	Number of days of disruptions reported	For how many days were your commuted roads flooded during and immediately in the aftermath of the Hurricane?
	Flood infrastructure	Yes – 1, No – 0	Before the Hurricane landed, was your residence in the proximity of flood control bayous and reservoirs?
	Flood zone	Yes – 1, No –0	Before the Hurricane landed, was your home located in a flood zone as designated by FEMA?
	Disruption risk	Low, High	Before the Hurricane landed, how severe would you have rated the following risks? - Flooding in your neighborhood
	Food shortage	Yes – 1, No – 0	Did you run out of food or water supply at home during the Hurricane?
	Boil water notice	Number of days of disruptions reported	For how many days did you have boil water notices?
	Store distance	Miles	Approximately, what was the distance from the closest grocery store to your house before the Hurricane landed.
Inherent Susceptibility	Family nearby	Yes – 1, No – 0	Before the Hurricane landed, did you have relatives or close friends in nearby areas to rely on their assistance in cases of emergencies?

Damage experience	Yes – 1, No – 0	Before the Hurricane landed, had you ever suffered any loss or damage from a natural disaster, either while living in your present home or a different place?
Community member	Yes – 1, No – 0	Before the Hurricane landed, were you a member of a local community organization (neighborhood club, social club, place of worship, religious group, cultural group
Residence duration	Number of Years Lived in Impacted Area	How many years had you lived in your current county before the Hurricane landed?
Mobility issues	Yes – 1, No – 0	Did any member of your household have difficulties with mobility in satisfying the needs due to a physical health condition before the Hurricane landed?
Chronic health	Yes – 1, No – 0	Did anyone in your household have a chronic medical condition before the Hurricane landed?
Disaster experience	Yes – 1, No – 0	Before the Hurricane landed, did you have previous experiences with any hurricanes, flooding, or any other types of natural disasters?
Age: 11-17	Number of household members between 11–17 years	How many people in your household were in the following age ranges before the Hurricane landed?
Age: 65+	Number of household members 65 years and older	
Age: 0–10	Number of household members under 10 years	
Residence type	Single family home, multiple units or apartment, other	What was the type of residence that you lived in before the Hurricane landed?
Home ownership status	Owned, rented	What was your household's home ownership status before the Hurricane landed?
Household size	Total number of household members	*Sum of reported members by age group
Income	Low (<$49,000), Middle ($50,000–$99,000), High (>$100,000)	Please specify your household annual income from all sources before the Hurricane landed?
Ethnicity	Minority, white	Which of the following options would best describe your household's race and ethnicity?

Protective Action	Preparation duration	Number of days preparing	How many days before the Hurricane landed did your household start preparing for the upcoming event?
	Evacuation warning	Yes – 1, No – 0	Did your household receive an early warning to evacuate?
	Underestimate disruptions	Yes – 1, No – 0	If you did not store enough food and water supplies for your household prior to the hurricane, what were your reasons?
	Underestimate storm	Yes – 1, No – 0	If you did not store enough food and water supplies for your household prior to the hurricane, what were your reasons?
	Stores visited	Number of stores visited during preparation	How many stores were visited before your household had enough food and water stocked?
	Storm awareness	Number of days	How many days before the Hurricane landed did your household first hear about the Hurricane? (Please put your answer in the number of days)
	Preparation actions	Sum of preparation actions performed (Secure generator, store food supplies, store water supplies, store fuel, prepare disaster kit, store medicine, secure house)	Which one of these preparation actions did your household take to prepare for the hurricane?
	Information sources	Sum of information sources used (TV and Radio, Agency contact, social media, Neighbors and local communities, Friends and family)	What were your primary sources of information for the condition of roads and road closures during Hurricane Harvey? (Please select your top three choices if more than three items applied to you) - Selected Choice
	Store supply shortage	Yes – 1, No – 0	If you did not store enough food and water supplies for your household prior to Hurricane Harvey, what were your reasons? (Please select all that apply) - Selected Choice
	Supply costs	Yes – 1, No – 0	If you did not store enough food and water supplies for your household prior to Hurricane Harvey, what were your reasons? (Please select all that apply) - Selected Choice
	Prep. impact	Low, High	Please consider your household's overall capabilities and select the degree of your agreement on the statement below: I believe that through preparedness prior to a disaster, my household can completely cope with infrastructure service disruptions without experiencing the negative impacts on our well-being

Preparedness	Low, High	Before the Hurricane, what was your perception of your household's preparedness?
Info reliability	Low, High	During and immediately after the Hurricane, were you able to gather reliable information about the road conditions and closures?
Power substitute	Yes – 1, No – 0	Did your household have any power backup or substitute?
Social media use	Yes – 1, No – 0	Did you use social media for sharing and receiving information about the Hurricane and your neighborhood?

STATISTICAL ANALYSIS

Decision trees are considered easily understandable and interpretable for general audiences (Burkart & Huber, 2021; Guidotti et al., 2018) and have been widely used across disciplines due to their robustness to outliers, skewness in data, ability to handle missing values without imputation, and non-parametric approach (Song & Lu, 2015). Decision trees show how combinations of multiple logical decisions lead to specific outcomes. The importance of pathway analysis not only the shows the combination of factors and their relative importance, (height is directly proportional to importance), but also the combination shows that, in the presence of other factors, certain, factors become significant.

A form of recursive partitioning called classification and regression tree analysis was chosen as the analysis method. The CART method was selected over alternative methods due to the interpretability of the model output and the algorithm's ability "to determine complex interactions among variables in the final tree, in contrast to identifying and defining the interactions in a multivariable logistic regression model" (Zimmerman et al., 2016). CART has been used previously to identify and understand the interaction among variables and the characteristics contributing to household food security in Ethiopia (Stephen & Downing, 2001).

The tree is designed to determine hardship experience outcomes due to critical infrastructure disruption impacts using variables related to protective action, household characteristics, and disaster communication features derived from the set of household-hurricane impact surveys. With CART analysis, “hardship pathways” determined by the model identify the sequence of binary splits that best sorts the sample by infrastructure hardship experience outcome. Beginning with the whole sample as one group, the procedure selects from all independent variables (Table 19) the one variable and the one cutoff for that variable that best splits the group into two subgroups, maximizing differences on the outcome, in this case, hardship outcome. Within each subgroup there is then again, the selection of the variable that best differentiates that subgroup by hardship status. This process continues, with binary splits flowing from binary splits, resulting in a tree with a root node (full sample) from which branches emerge, and derivative nodes at each point where a subgroup is further split until there are terminal nodes from which no more splits can be made (e.g., no significant additional differentiation on the outcome is possible).

The household infrastructure disruption dataset was used to train multiple CART trees using the Rpart package in R (Therneau & Atkinson, 2015) with 10-fold cross-validation. The hardship impact pathways due to the following critical infrastructure systems were modeled: (1) Power, (2) road transportation, (3) water, (4) food. The effect of income and ethnic minority status were modeled by running the subsequent CART model on the data's subsets representing each population group. Income group classification was simplified to low, medium, high categories, while ethnic minority groups were classified as households reporting to be non-white in the survey.

A total of 24 CART models were developed to represent the different hardship impact pathways for each income and ethnic group, in addition to five CART models representing the well-being impact pathways for each infrastructure system. Using an 80:20 train-test split of the data, testing of the trained models was performed to assess the models' sensitivity on new data and confirm the validity of the CART decisions and prediction of hardship. The classification accuracy (ACC), sensitivity (SEN), and specificity (SPE) were used to assess the performance accuracy of the models. The variable importance across each model configuration was ranked and compared across the infrastructure systems and population groups, measured by the Gini index.

Performance Accuracy Models:

$$ACC = TP + TN / TP + TN + FP + FN \quad (1)$$

$$\text{SPE} = \text{TN} + \text{FP} * 100\% \quad (2)$$

$$\text{SEN} = \text{TP} + \text{FN} * 100\% \quad (3)$$

RESULTS

CART Model Performance

A total of 24 CART models were developed and implemented in R to identify vulnerability pathways distinguished by infrastructure service type and household demographics. A summary of the final decision node outcomes, including the total number of nodes falling into each hardship level category are provided in Table 20, and performance statistics (accuracy, sensitivity, and specificity) for each model are provided in Table 21. Overall, the models are strongest in predicting *high* and *low* levels of hardship, whereas prediction of *moderate* hardship compromises model accuracy. Model performance, which could be influenced by the data sample size, varies across each model. The **no-information rate (NIR)** averages to 73%. This is the accuracy achievable by always predicting the majority class. The p-values indicate that the ranges of the NIR are sufficient for the model to offer significantly better performance over the no-information rate.

Empirical observations based on the proportion of *high hardship* terminal nodes to total tree nodes used in each model are also summarized in Table 20. There is some indication that water disruptions disproportionately impacted low-income and minority households, given the higher relative proportion of *high hardship* terminal nodes found in the decision trees for these two groups. For hardship experiences resulting from disruptions in electricity services, there are no *low hardship* outcomes for all household groups studied. All households impacted by power disruptions experienced *moderate* to *high* levels of hardship. Households experiencing disruptions to food infrastructure services were more likely to have hardship outcomes resulting in *low* to *moderate* impact across all groups. In general, there is no significant trend in the *number of* nodes and *proportion of terminal high hardship nodes* demonstrated in this Table 3.

Further analysis of the variable selection and importance for each model distinguished by infrastructure system service and population segment was implemented to identify any disparities in the hardship pathways. The following sections address disparities in hardship pathways by income and ethnicity groups.

Table 20: CART tree overview of decision node classification by hardship level and vulnerability type.

Infrastructure system		Decision node outcome				Node classification (% of unique nodes)		
		High	*Moderate*	*Low*	*Total*	*Inherent susceptibility*	*Disruption exposure*	*Protective Actions*
Water	All	6	6	6	18	0.385	0.231	0.385
	Minority	5	2	1	8	0.125	0.250	0.625
	White	3	3	3	9	0.167	0.500	0.333
	Low income	4	3	3	10	0.375	0.375	0.250
	Middle income	1	2	2	5	0.250	0.500	0.250
	High income	1	1	2	4	0.500	0.500	0.000
Power	All	2	4	0	6	0.222	0.222	0.556
	Minority	4	6	0	10	0.571	0.286	0.143
	White	5	12	0	17	0.400	0.200	0.400
	Low income	6	5	0	11	0.222	0.222	0.556
	Middle income	4	6	0	10	0.500	0.000	0.500
	High income	2	4	0	6	0.429	0.286	0.286
Food	All	2	4	3	9	0.143	0.571	0.286
	Minority	2	5	3	10	0.375	0.375	0.250
	White	5	4	6	15	0.444	0.333	0.222
	Low income	3	4	3	10	0.250	0.500	0.250
	Middle income	2	3	3	8	0.400	0.000	0.300
	High income	2	1	2	5	0.167	0.333	0.500
Transportation	All	2	0	2	4	0.000	0.333	0.667
	Minority	6	3	4	13	0.364	0.273	0.364
	White	5	2	3	10	0.250	0.500	0.250
	Low income	4	4	3	11	0.300	0.300	0.400
	Middle income	5	8	8	21	0.350	0.400	0.250
	High income	6	3	4	13	0.250	0.417	0.333

Table 21: Model performance statistics: accuracy, specificity, sensitivity based on high hardship class.

Infrastructure System	Overall Statistics				
	Subgroup	*Accuracy*	*Specificity*	*Sensitivity*	P-value (Acc> NIR) *
Water	*All*	0.86	0.69	0.86	< 2.2e-16
	Minority	0.63	0.82	0.55	0.00
	White	0.66	0.83	0.72	< 2.2e-16
	Low income	0.65	0.66	0.81	0.00
	Middle income	0.61	0.68	0.60	0.00
	High income	0.68	0.85	0.84	0.00
Power	*All*	0.73	0.94	0.40	0.00
	Minority	0.81	0.92	0.46	0.03
	White	0.75	0.89	0.57	0.00
	Low income	0.75	0.90	0.57	0.00
	Middle income	0.77	0.85	0.70	0.00
	High income	0.76	0.90	0.48	0.02
Food	*All*	0.66	0.83	0.85	< 2.2e-16
	Minority	0.67	0.94	0.56	< 2.2e-16
	White	0.73	0.91	0.70	< 2.2e-16
	Low income	0.67	0.92	0.63	< 2.2e-16
	Middle income	0.71	0.88	0.62	0.00
	High income	0.69	0.86	0.56	0.59
Road/ Transportation	*All*	0.54	0.82	0.55	< 2.2e-16
	Minority	0.61	0.74	0.70	< 2.2e-16
	White	0.57	0.96	0.40	0.00
	Low income	0.63	0.77	0.72	< 2.2e-16
	Middle income	0.66	0.91	0.50	< 2.2e-16
	High income	0.62	0.95	0.44	0.00

***** NIR: No information rate

Variable Importance and Variables Used In Model Constructions

All CART trees are included in Appendix C. Variable importance analysis was carried out to assess the average decrease in the nodes' impurity measured by the Gini index during the construction of the CART models. Fig 15 presents the results of this analysis for infrastructure service with the variables ranked by their Gini importance.

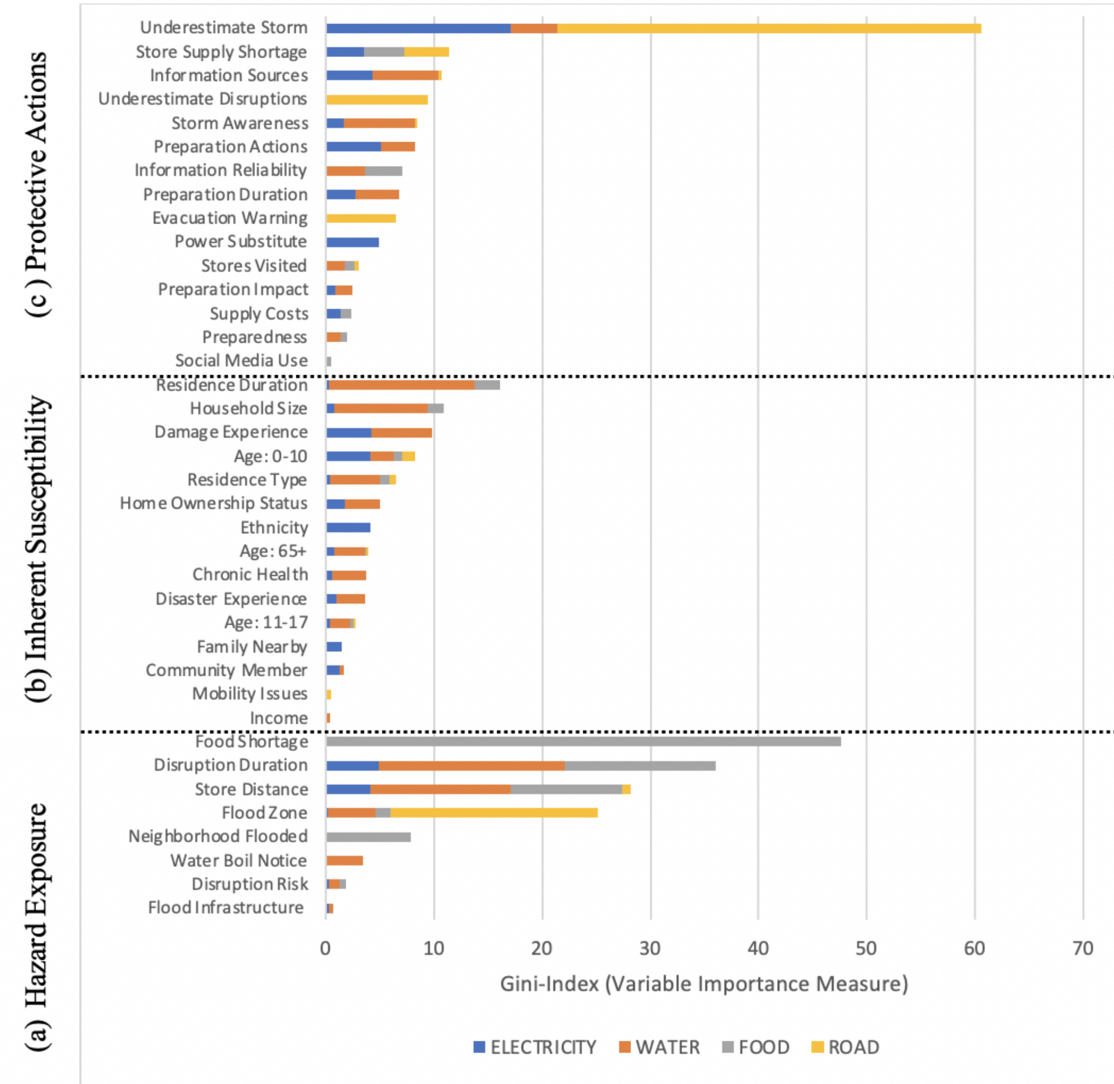


Figure 15: Variable importance in the CART model for all population groups (combined dataset). Variables are classified by (a) hazard exposure, (b) inherent susceptibility, (c) protective actions.

Disparity Pathways Across Income Groups

Electricity

Disparities in hardship pathways due to electricity service disruptions with respect to income group levels can be tied to (1) underlying health conditions, (2) information communication, (3) underestimation of storm impacts, (4) accessibility to grocery stores. The pathways demonstrated by the CART model results indicate that there is a discrepancy in the set of important variables that determine hardship outcomes in households by income group level (Fig 15). For high-income households, four pathways lead to high hardship outcomes. For high-income households, having a chronic health condition appeared to be the greatest determining factor of hardship due to power outages. High-income households with a resident with a chronic health condition were also more likely to experience heightened hardship if they also live in a FEMA-designated flood zone. Of those households without a chronic health condition, the distance to the grocery store (≥ 6.5 miles) is the secondary indicator of hardship experience in high-income households. The third hardship pathway for high-income households involves households without a chronic health condition, living in closer proximity to the grocery store (≤ 6.5 miles), but which indicated less information-seeking activity (less than two information sources), and were homeowners by mortgage. In the fourth hardship pathway, it is apparent that seeking information from more than two sources can potentially play a role in mitigating hardship experiences during a power outage. Those seeking more information sources, however, still experienced high hardship if they were newer residents of the county (< 5 years) or conversely, greater than 55 years of age, and had a shorter forewarning time to prepare for the storm.

Hardship pathways for low-income households indicated a lack of preparation for the hurricane due to underestimation of the storm's potential impact. This can indicate general lack of awareness about incoming risks due to communication barriers or level of importance to prepare and to anticipate the severity of the storm. Despite underestimating storm impacts, observing more preparation actions, and having more awareness of the storm arrival, gathering information from two or more information sources about the storm, these preparations did not appear to mitigate hardship impacts in minority households. A segment of the lower-income population that underestimated storm impacts similarly engaged in fewer protective action measures (< 1), experienced 3.5 days or more of power service disruptions. If power outages or disruptions occurred for less than 3.5 days, low-income households impacted by outages were more likely to live 4.5 miles or further from the nearest grocery store.

If low-income households did not underestimate the storm, their hardship due to power outages can be associated with the extent of their storm preparations. Store visitation in this case does not necessarily indicate greater preparation, but possibility greater difficulty in accessibility to critical supplies to prepare for the approaching hurricane. If the number of stores visited did not fall on a severe hardship pathway, households in low-income groups experiencing hardship were likely to live in single-family homes 14 miles or more to the nearest grocery store. Living in a closer radius to grocery stores and living in a housing community of multi-unit dwellings appears to reduce the hardship experienced in low-income households due to power disruptions.

There is a strong indication that middle income households impacted more severely by power outages were more likely to be from elderly population groups. Their hardship pathways were characterized by less preparation time, under-preparedness due to less awareness about storm landfall, and prior disaster experience. While the households were more likely to be members of community clubs or organizations, this did not appear to mitigate the severity of hardship experienced. Furthermore, being a community member may not necessarily increase the household-awareness of storms.

Water

Disparities in hardship pathways due to water service disruptions with respect to income group levels can be tied to (1) household size, (2) food desert or distance to grocery store, (3) disruption duration, and (4) social connectedness (Fig 16). Low-income households were more likely to experience boil-water notices, which contributed to their hardship experiences.

Meanwhile middle- and higher-income households did not have boil-water notices as contributors to their hardship experience. This can indicate that lower-income households are at greater risk of water contamination problems during disruptive events. Boil-water advisories often result from other events, such as water line breaks, treatment disruptions, power outages, and floods. Lower-income groups also indicated that the lack of social connectedness by means of family and friends nearby contributed to greater hardship outcomes. For higher-income households, having family or friends nearby as social connectedness resources did not appear to mitigate hardship experience. If higher-income households had prior disaster experience and fewer than four household members at the time of the hurricane landfall, they were less likely to experience detrimental hardship impacts compared to larger households that did not have prior experience with natural hazards. Middle-income households that held residency in their respective county for twelve or more years and lived further than 1 mile from the nearest grocery store were more likely to experience greater hardship due to water disruptions. Low-income households were more likely to be affected if the household was greater than three members. Larger household size makes it more difficult to store enough water for the needs of all members.

Early preparation is an important mitigating factor in hardship. Households that experienced water boil notices for one or more days experienced little to no hardship impact due to water disruptions if they had at least eight days to prepare. Households that experienced less than one day of water boil notices experienced little to no hardship due to water disruptions if they had at least five days to prepare for the storm. Grocery store distance does appear to mitigate the levels of hardship experience in these cases. For example, households within 9.5 miles of the grocery store that had at least eight days to prepare for the incoming storm were more likely to avoid extensive hardship if they experienced disruptions to water supply. If a household had fewer than eight days to prepare and felt the information on water outages was unreliable, their hardship was mitigated if the household had less than three occupants at the time of the storm. It cannot be concluded from the results of this CART model that *Information Reliability* is a mitigating factor of hardship experience. Despite receiving reliable information, households still experienced high levels of hardship. The pathways of the tree indicate some type of relationship between household size and information reliability perception.

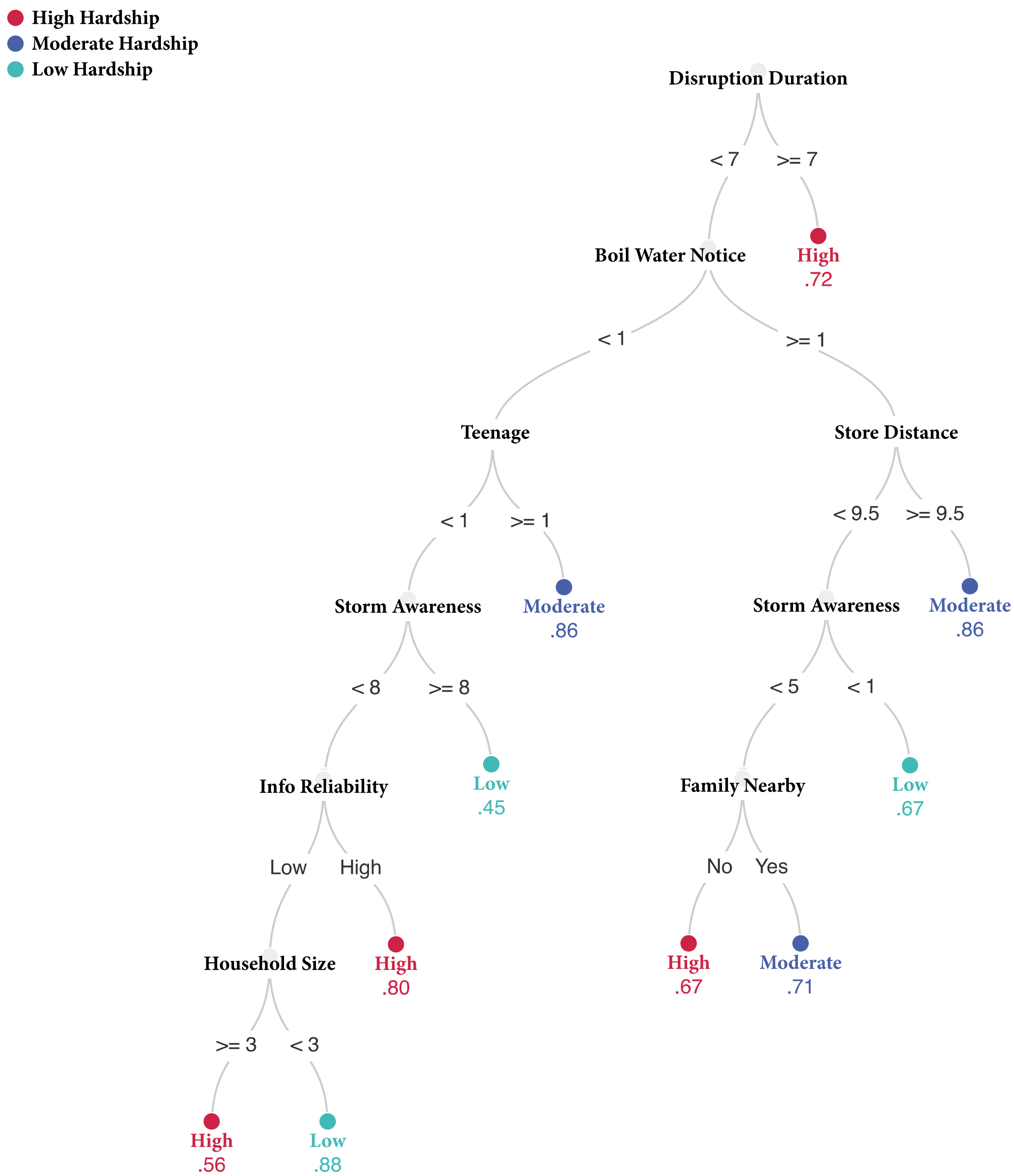


Figure 16: CART decision tree for low-income households experiencing water disruptions

Food

Disparities in hardship pathways due to water service disruptions with respect to income group levels can be tied to (1) household demographics (ethnicity), (2) food desert or distance to grocery store, (3) exposure to hazards (flooding). Running out of food supplies is the common denominator of high hardship pathways across all income groups. Most importantly, there was only one hardship pathway for food disruption hardship in high-income households. However, high-income households that experienced moderate hardship lived more than 2 miles from their nearest grocery store and needed to visit more than three stores to purchase needed supplied in preparation for the storm.

Middle-income households that did not experience food shortages at home experienced supply shortages at the stores resulting in moderate hardship. If supply shortages were experienced, food disruptions lasted more than four days. Low-income households similarly showed running out of food at home as the greatest contributor to household hardship due to food service disruptions. However, in low-income households, there is a connection to hazard exposure due to road flooding. Low-income households were more likely to experience flooded roads in their neighborhoods, which can indicate possible barriers to food accessibility in the aftermath of the hurricane, and in return, prolong food supply access disruptions, as the pathway in Fig 17 indicates. High-hardship pathways for low-income households show that being beyond 6.5 miles from the nearest grocery store is an important variable. This distance could have in turn contributed to running out of household food supplies. In contrast to high-income households that visited more stores in the preparation period, low-income households visited fewer stores, implying possible limited accessibility to grocery stores due to distance or geography.

In low-income households, several factors contributed to mitigating the extent of hardship experienced due to disruptions to food supply accessibility. These factors include: (1) having less head time about the incoming hurricane or storm (≥ 5 or more days), (2) being new residents to the area (less than thirteen years of residency), and (3) being from a white household. Holding income constant, the final point indicates some level of ethnic disparity in food disruption hardship.

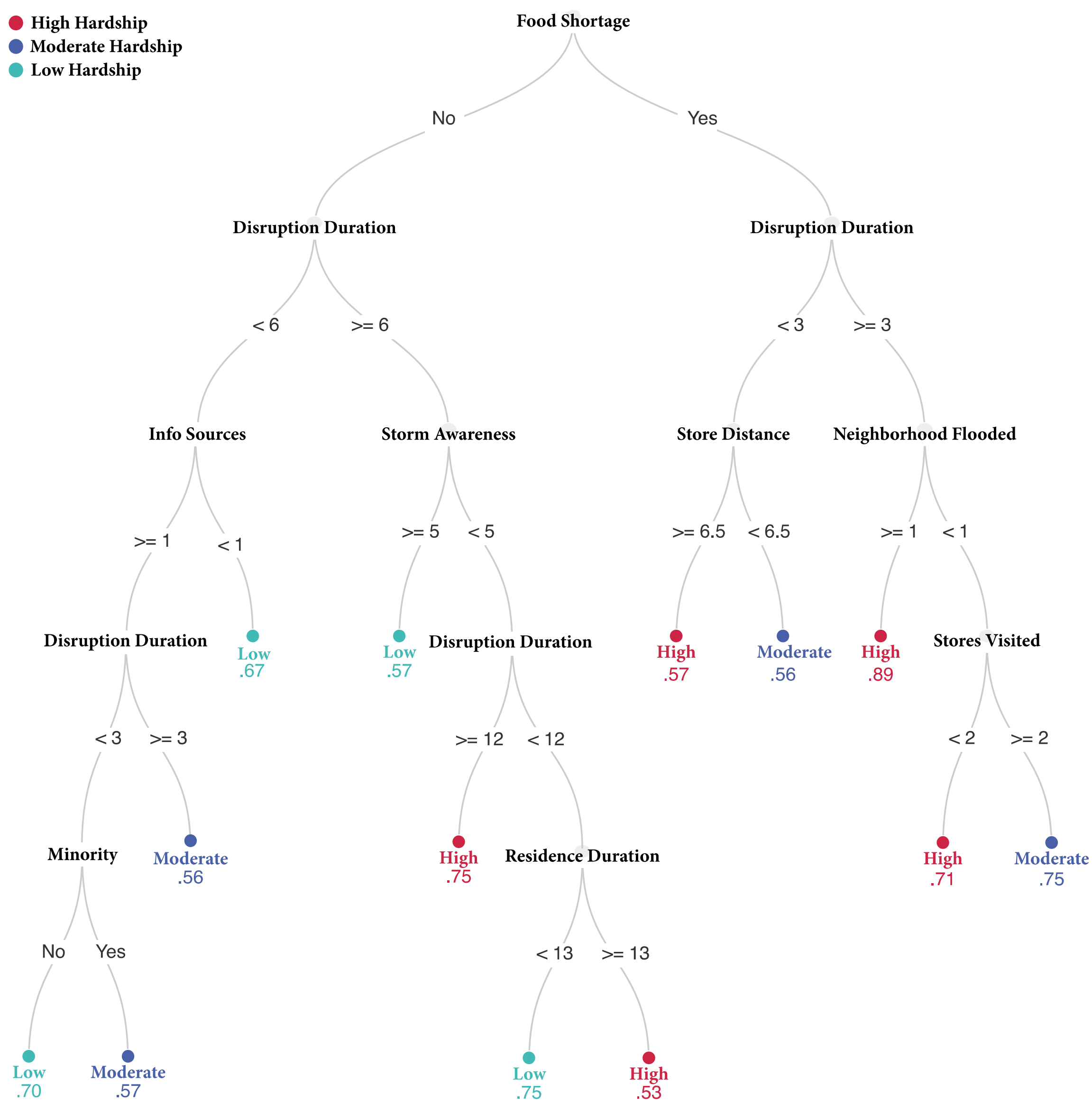


Figure 17: CART decision tree for low-income households experiencing food infrastructure disruptions.

Transportation

Disparities in hardship pathways due to transportation service disruptions with respect to income group levels can be tied to (1) underestimation of storm impacts, and (2) exposure to hazards. Hardship due to transportation disruptions is highly characterized by physical disruptions and hazard exposures across all income groups. Higher income households were more likely to have prior mobility-related health challenges, have experienced neighborhood flooding, and live near storm water infrastructure and in a FEMA-designated flood zone. This group also had prior experience with damage due to hurricanes or other natural disasters, which indicates that risk exposure has not changed present approaches to disaster preparation. High-income households that experienced greater hardship due to disruptions were more likely to underestimate storm impacts of destruction.

Middle-income groups similarly underestimated the storm impacts, experienced flooding in their neighborhood but were more likely to be from minority racial groups. Low-income groups were more likely to underestimate storm impacts and have limited belief in the effectiveness of storm preparation. It appears that disruptions to roads are more likely to affect higher- and middle-income households. Perhaps higher- and middle-income households depend upon road transportation. As a result, their hardship experiences are different from households from low-income areas.

Disparity Pathways Across Minority Groups

Hardship pathway differences were further explored by ethnicity group controlling for all other social and demographic factors.

Electricity

Underestimating the storm is the most prominent variable in determining hardship outcomes in minority households experiencing power hardship. Both low- and high-income minority households were predisposed to high hardship outcomes despite not underestimating the storm impact. This is the most prominent disparity related to the discrepancy in hardship pathways between minority and non-minority groups. Minority households were also more likely to house children under 10 years old at the time of the impact and lacked relatives or close friends nearby. Minority households experienced shorter preparation time and less prior awareness, and overall, underestimated the impacts of the storm.

Non-minority households similarly reported that they underestimated the storm impact, this being the most significant variable in determining hardship due to power outages. The duration of power outages or disruptions appears to be a prominent factor in the pathway of hardship in non-minority households, whereas this was not the case for minority households. Household size is another significant factor in determining hardship in non-minority households due to power disruptions. Not having a power back-up or substitute was another significant factor on the hardship pathway for non-minority households. Non-minority households had longer duration for preparation, whereas for minority households, less preparation time factored into their hardship experience. There were no minimal hardship pathways for this population segment; all hardship pathways fell in the range of moderate or a lot of hardship. Household size was also a determinant of whether a household would underestimate the storm: households of fewer than five members would be likely to underestimate storm impacts.

Water

Most notably, minority households were more likely to experience water-boil notices compared to non-minority households (Fig 18). Water-boil notices did not appear on the hardship pathways for non-minority households. Duration of disruption was the most prominent determining factor for hardship experience in both minority and non-minority households. Non-minority households experienced hardship due to duration of water-boil notices, distance to grocery stores, and lack of social connectedness in terms of family and friends.

Minority households appear to be impacted by water disruptions due to barriers to preparation experienced prior to the storm landfall and impact, as indicated by being on the hardship pathway. These barriers include supply shortages at stores and financial considerations. Minority households experiencing greater hardship due to water outages also had larger households, owing to household demand and responsibility to provide water for more household members. Minority households experiencing water hardship also had prior experience with disasters and damages, indicating perhaps they are unable to relocate to areas where disaster risk is reduced. Having no prior experience with disasters, particularly with damages, indicative of living in a low-hazard area, appears to be the only hardship-mitigating factor for households experiencing water-outage hardship.

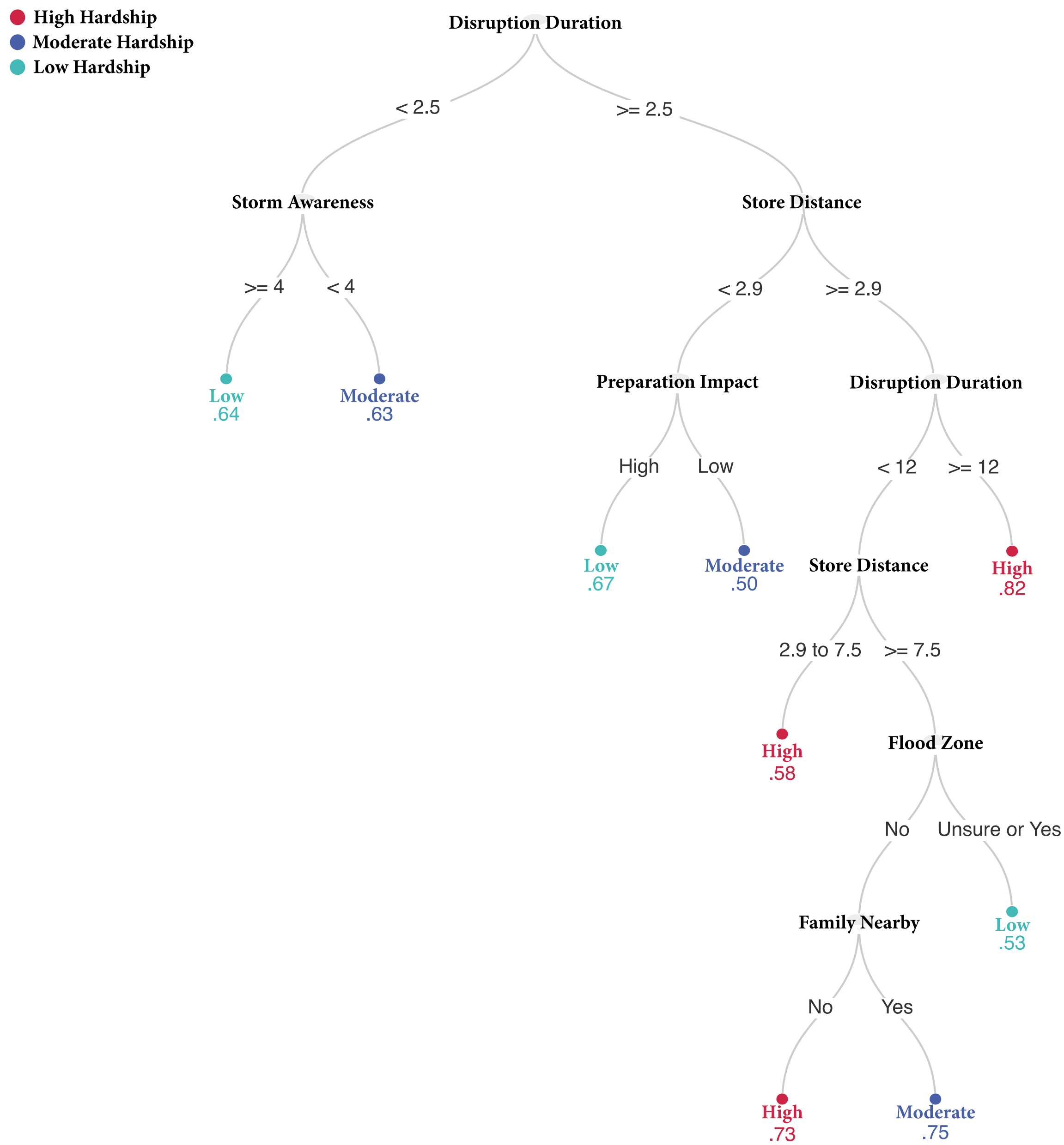


Figure 18: CART decision tree for white households experiencing water disruptions

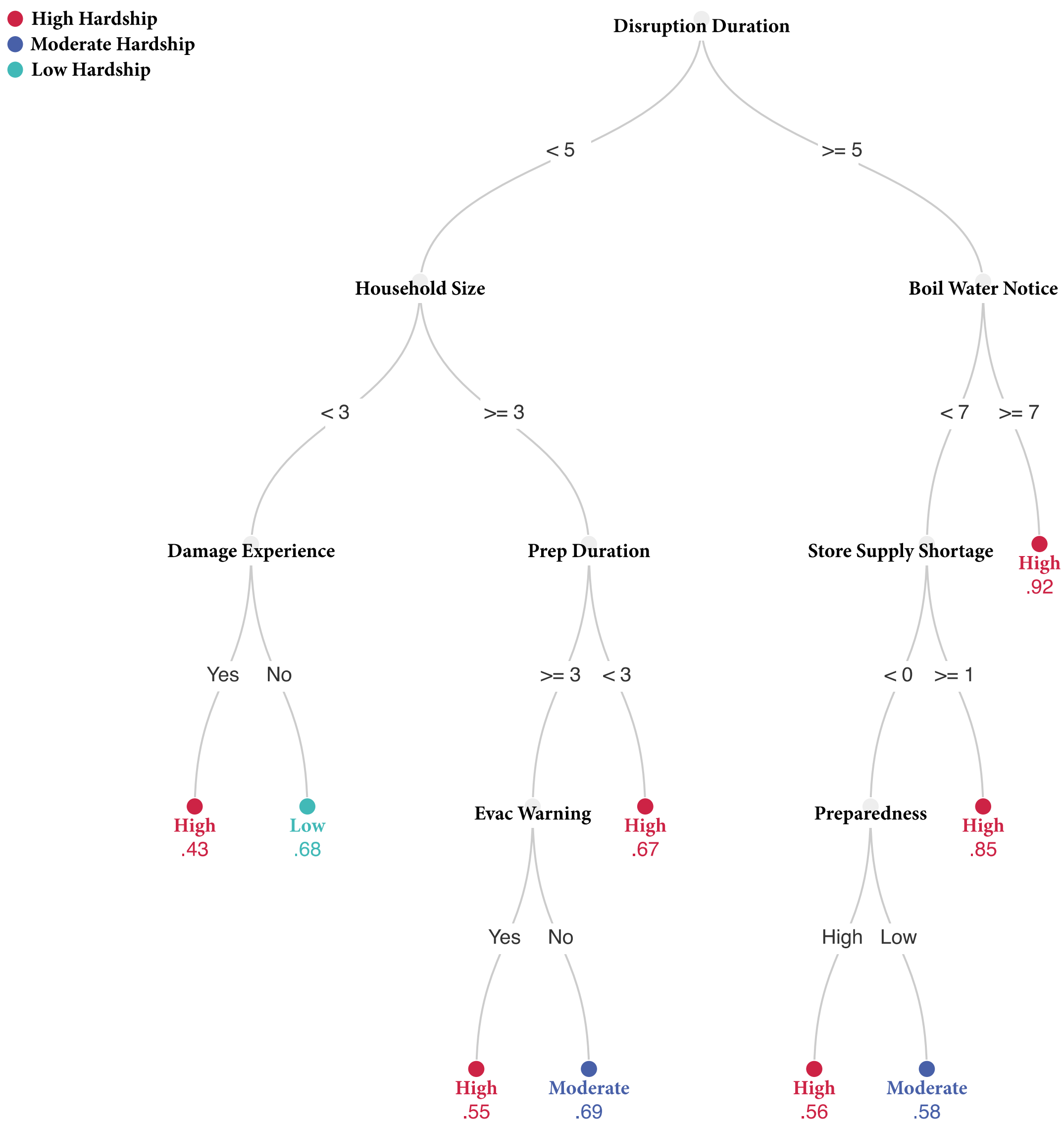


Figure 19: CART decision tree for minority households experiencing water disruptions.

Food

Both minority and non-minority households that experienced significant hardship due to food disruptions first experienced shortages in food supply at home. Minority households experiencing hardship were also more likely to be from lower-income backgrounds; however, the duration of the reported disruptions to food infrastructure service accessibility does not appear to be related to minority households experiencing food shortages at home. A minority household experiencing six days or more of disruption did not report a food shortage at home. The intolerance for food disruptions in households that reported food shortages is indicated by the shorter experienced duration of food disruptions and distance from their nearest grocery store: minority households that experienced food shortages at home experienced three days or more of disruptions and lived more than 6.5 miles from the nearest grocery store.

Non-minority households displayed more heterogonous pathways to hardship (Fig 19). Similarly, disruption time was a primary factor for determining hardship. However, households experiencing hardship experienced food shortages at their grocery store during the preparation phase. Household size also appeared to be a prominent factor akin to water hardships, where the greater the household size, the greater the demand for food and stress on limited resources. Non-minority households were similarly from low-income backgrounds and were more likely to have household members with a disability or mobility health issue and lived in an apartment or multi-unit complex. These results indicate that non-minority households who experienced high hardship had attributes (such as low income) that made them more inherently susceptible to food disruptions.

Transportation

Households experiencing significant hardship due to road disruptions were more likely to be exposed to physical hazards and to underestimate the overall severity and impact of the hurricane. Minority households impacted were more likely experience flooding in their neighborhoods, whereas for non-minorities, this was not a factor of hardship. Furthermore, minority households are compounded by other inherent susceptibility factors of having a chronic medical condition, whereas non-minorities were more likely to have children under the age of 10. Minority households also expressed that they experienced barriers to preparation, which have an association with their transportation hardship experience. Non-minority households that experienced hardship lived in FEMA-designated flood zones.

DISCUSSION

This study used pathway analysis to evaluate the different combinations of *inherent susceptibility*, *protective action*, and *risk exposure* factors that cause varying levels of hardship outcomes in households impacted by infrastructure service disruptions during major hurricane events in the United States. We first hypothesized equifinality (i.e., the same end state can be reached by many different means) in the processes that lead household systems to experience disparities in hardship impact during service disruptions. Second, we hypothesized that the pathways would differ according to both the service disruption type (i.e., power outage versus water outage) and the subpopulation group (i.e., income versus ethnicity). From the analysis, we observed multiple patterns of variable combinations that shape heterogeneous pathways through which households with different characteristics become more vulnerable to service disruptions.

A novel contribution of this study is uncovering of the heterogeneous pathways to hardships due to infrastructure service disruptions enabled by CART analysis. CART has advantages over bivariate statistical analysis, such as Pearson correlations. With correlation analysis, the standalone relationship and magnitude of the relationship between two variables can be determined. With a multivariate decision-tree based methodology, a sequential relationship based on a set of threshold rules can be determined. The CART trees show the importance of variables in terms of their positioning and sequence in the tree and by the rules set by the tree nodes at each split.

Reducing the societal impacts of infrastructure service disruptions using a human-centric infrastructure approach means addressing disruptions through approaches that heed importance to infrastructure system improvements and improving the capabilities of households to be resilient in times of service failures. Standard infrastructure resilience emphasizes fail-safe systems, while human-centric infrastructure resilience focuses on making systems “safe to fail” by reducing societal impacts of service disruptions. Infrastructure resilience becomes human-centric when decisions are based on reducing the susceptibilities of the households to system failures by improving their capabilities for protective actions and improving infrastructure. A combination of robust infrastructure systems and resilient households are essential for reducing the societal impacts of infrastructure on a household, particularly those of vulnerable population groups.

While households experienced a range of hardship outcomes varying from low, moderate, and high impact, discussion of the results focuses on the pathways leading to high hardship outcomes and a discussion of the characterization of the factor combinations within the identified pathways. The discussion is organized by addressing the key findings of this study and how these findings can be transformed into recommendations for relevant stakeholders in infrastructure and disaster management agencies. Whereas the discussion of the critical findings and results from the presented analysis has focused on pathways leading to *high hardship,* there were vulnerable population groups that experienced low hardship outcomes despite experiencing prolonged service outages. The decision trees can be used in a similar way to identify the differential factors that mitigate hardship experiences in vulnerable population groups. The pathways to low-hardship outcomes highlight a particular set of variables that assisted households in coping with service outages. This finding disrupts the myth that all vulnerable populations experience high hardship due to service disruptions because they are inherently vulnerable or have barriers to protective actions

Synthesis Of Findings from Different Pathways

Overall, household experiences of hardship due to hurricane-induced infrastructure disruptions were associated with combinations of factors for different types of households and often occurred at the intersection of multiple characteristics spanning various inherent susceptibility factors, extent of protective actions taken, and hazard exposure factors. The key findings and implications of the results are discussed below.

Inherent susceptibility, protective action, and risk exposure related factors and their relative importance vary across different subpopulation groups and different infrastructure services.

The CART trees helped distinguish the level of importance of variables in determining hardship outcomes due to infrastructure service disruptions in different income and ethnic groups. When assessing the hardship pathways without stratifying the data into different income and ethnic group samples, the factor *Electricity outage duration* occurs as a splitting node in the middle of the tree, preceded by households who *Underestimated the storm impact* and had

Children. The pathways change when the CART model is implemented with the stratified sample of minority households only: *Electricity outage duration* shifts to the final node on the tree, signifying the drop in importance of electricity outage duration in characterizing hardship experiences in minority households. Furthermore, the relationship between disruption duration and hardship is not found to be linear. Minority households experiencing four or more days of power disruptions were more likely to have experienced moderate levels of hardship due to the electricity outages. When the data is stratified by income group level, *Disruption duration* is no longer a significant variable in the decision tree for middle- or high-Income groups. It is therefore evident that the duration of disruptions in electricity services is more prominent as a factor of hardship impact in low-income households regardless of ethnic background. It is important to highlight that in the case of households that experienced power disruptions during the hurricane events, no households experienced low to no hardship. This finding indicates the susceptibility of all households to power disruptions, holding sociodemographic factors aside. Similarly, in the case of *Preparation duration*, non-minority households were more likely to have longer durations of preparation. However, it did not appear to factor into their extent of hardship experienced. Conversely, for minority households, less preparation time factored into their hardship experience, exemplifying a contrast in the level of preparation between two population groups.

Information-seeking behavior also appears to have differing roles in the pathway to hardship experience, depending on the service and population segment at hand. For an example, lower information seeking activity during food service disruptions mitigated hardship experience in minority households. In the case of information-seeking regarding food service disruptions, it appears that greater search activity is indicative of the lack of readily available information about food service disruption status and the need to exhaust more than one information source to fulfill satisfactory situational awareness about food service disruptions. In some cases, the onset of disasters does not permit enough time to communicate risks to inhabitants of areas.

When developing hardship mitigation strategies that are guided by human-centric thinking, this finding is important because different intervention points can effectively address the influencing factors of different hardship outcomes. Addressing hardship impact will depend on a combination of different disruption tolerance levels, inherent household factors, and built-environment failures or insufficiencies.

For certain infrastructure system services, variables of preparation behaviors will be more critical in determining households' hardship outcomes. Therefore, the set of hardship mitigation strategies for reducing the impact disparity gap will be specific not only to the population group affected but the type of infrastructure service. Arguably, prioritizing hardship attributes can have the potential to improve the overall household-level resilience to more than one type of service disruption. For example, prioritizing the awareness and accessibility to protective actions can help households prepare for disruptions in food and transportation services and bolster the resilience of households against future disruptions.

The effect of factors in the hardship pathways depends on the presence or absence of other factors.

Certain hardship pathways are governed more by factors that could be improved by investing in physical infrastructure improvements, whereas other pathways indicate the need to address household-level deficiencies related to protective action behaviors and inherent susceptibility. There is a bidirectional relationship between infrastructure systems and households as empirically determined by J. Dargin et al. (2020). Therefore, addressing insufficiencies in physical infrastructure systems can improve the preparation of households and reduce their exposure to disruption impacts. Household resilience can be improved by addressing their inherent susceptibilities and preparation deficiencies by adapting a ‘safe-to-fail’ approach to infrastructure resilience. This approach highlights the nature of the relationship between inherent susceptibility, protective action, and hazard exposure factors, and how they collectively lead to hardship. Factors of social connectedness would be significant depending on the infrastructure service that is disrupted, and the subpopulation groups impacted. In some situations, depending on the type of infrastructure system and population group experiencing the disruption, family and friends living in the vicinity of the affected household at the time of the hurricane impact and service disruption played a mitigating role in the final hardship outcome. However, in different scenarios, the measure of social connectedness was either absent or had an opposite effect. A similar trend was observed with regards to information-seeking activity and reliability: the extent of information-seeking activity depends on the infrastructure service disruption type and population group. Despite having access to reliable information, a household would still experience high levels of hardship due to other factors. In this pathway, it can be determined that expanding information accessibility may not be a hardship mitigation intervention strategy for certain population groups or service disruption types.

The results of this study further show that even within different population groups (i.e., income levels and ethnic and racial groups), various pathways to hardship exist that demonstrate the diversity and prevalence of different vulnerability profiles for households. This has been explored earlier by Daellenbach, Parkinson, and Krisjanous (2018), who used a clustering algorithm to determine different market segments of the population according to their behaviors surrounding perspectives of risk and preparedness for a hurricane event, using market segmentation and the theory of planned behavior. In the conclusion of the study, Daellenbach et al. (2018) identified four unique population segments: The *unprepared and uninterested* segment may be encouraged by associating preparation tasks with benefits *other* than disaster resilience. *Willing but could do more* may respond to information highlighting that government support may not be enough in a disaster. For the *it's just too difficult* segment, barriers need to be addressed, lowering costs of preparation, and changing perceptions of difficulty. Those in *knowing, interested, and prepared* could be encouraged to help spread the word of the importance of preparation. In the case of the studied CART models, we can similarly use the pathways to characterize the households into different vulnerability profiles. There are different types of households in each category. This gives us insights into different service disruption hardship groups. As an example, for minority households impacted by electricity disruptions, there are a total of three high-hardship groups identified from the CART tree, as follows:

Pathway 1: Underestimated storm impacts, underprepared

Pathway 2: Prepared but still impacted: less information search: needed to visit more than one store, far away from grocery stores, single family homes.

Pathway 3: Prepared but needed to check more information sources but did not or could not.

The pathway analysis confirms that in some pathways to hardship, inherent susceptibility factors, including income, race, health condition, and household size, can influence the segment into which segment a household falls. Low-income households experiencing electricity hardship could be traced back to lack of sufficient preparation, indicated by the node decision of less than one preparation activity performed prior to the storm landfall. Conversely, preparing equal to or greater than one preparation actions (Prep. actions in Table 19) did not necessarily mitigate hardship experience due to electricity outages, for example. Those that prepared more in terms of preparation activities and having equal to or greater than five days of preparation prior to the storm landfall still experienced the highest levels of hardship. This result was related to information-seeking activity (fewer than two information sources were sought out by the household), or, in the case more than two information sources were used, the household was more likely to be from a minority background. Enduring food shortages at home is the primary predictor of hardship experience in households experiencing disruptions in food services during hurricane events. Regardless of income or ethnic background, experiencing food shortage at home because of lack of accessibility to food suppliers will result in high hardship due to food supply shortages. The pathway evaluations show, however, that even if a household does not experience a food shortage at home, the household can still experience high levels of hardship.

The hardship pathways identified provide recommendations for improving infrastructure systems for equitable infrastructure resilience

The proposed model facilitates both tactical and strategic decisions for infrastructure managers, relief practitioners, and other stakeholders. The evaluation of hardship pathways helps to identify recommendations for human-centric infrastructure system practices that can address disparities in disruption impacts within communities. The analysis showed that certain pathways are dominated more by certain categories of factors, indicating whether discrepancies in hardship experience can be addressed with infrastructure-level interventions, household-level interventions, or a combination of both. The pathways demonstrated by the CART model outputs can be leveraged to help: (1) infrastructure managers, planners, and public officials to better understand and incorporate the expectations and needs of vulnerable populations in infrastructure prioritization and resource allocation; and (2) households to build capacity to better cope with infrastructure service disruptions in disasters. There are three hazard mitigation scopes demonstrated by the conceptual framework: exposure reduction, enabling protective actions, understanding inherent susceptibilities to service disruptions.

Recommendations for equitable infrastructure resilience improvements

Prioritization of service restoration based on social vulnerability.

Fail-proof approaches for resilience and prioritization ignore the key societal impacts that failures and disruptions have on households. Consequently, the application of such approaches would lead to restorations and infrastructure improvements that do not improve or reduce the social impacts of infrastructure services in an socially equitable way (Coleman et al., 2020b; J. S. Dargin & Mostafavi, 2020; Esmalian, Dong, & Mostafavi, 2020; Kane & Vajjhala, 2020).

According to Clark et al. (2018), a human-centered approach to infrastructure prioritization identifies infrastructure systems that ensure people have their most basic needs met during a disaster (Clark et al., 2018). Using Maslow's hierarchy of needs, it is suggested that there are certain services that must be prioritized, while less urgent needs, while still important, can be sacrificed temporarily during disasters (Clark et al., 2018). While their work identifies the critical infrastructure systems that require prioritization during disasters, their framework is unable to address the population-specific disparities in service gaps and impacts. An aspect of infrastructure prioritization that also requires attention vis-a-vis resilience is the prioritization of service restorations. This infrastructure improvement recommendation involves not only prioritizing infrastructure systems based on their criticality of supporting human capabilities, but also prioritizing service for populations with the most needs and disparate impacts. Infrastructure agencies can identify those areas right before disaster and prioritize them for restoration: for example, areas with low income and large household sizes. Infrastructure agencies can focus on minimizing the outages for these low-income households. For example, prioritization and restoration services can focus on communities who had little warning of the impending disaster; and thus, little time to adequately prepare for the potential service disruptions.

Improve facility distribution and resource accessibility for susceptible households.

Exclusionary zoning, imbedded in land use and transportation policies since the 20th Century, has allowed policy makers and leaders to overlook or intentionally omit the needs of lower-income households and minority communities (those that are historically most susceptible to disasters) when building and maintaining infrastructure systems (Bartos et al., 2016). As a result, and as indicated by the hardship pathways in this study, the accessibility to critical services and their distribution to susceptible households needs to become a focus of the approach to improve infrastructure system resilience.

Some of the hazard exposure factors, such as distance to grocery stores (an indicator of food accessibility), can indicate the need for improved access to grocery stores by means of road accessibility or installation of additional facilities. Emergency response can use this information to guide intervention decisions, where areas with limited food accessibility as measured by distance to grocery stores should be prioritized in receiving food relief supplies. Based on the results and pathways, certain social demographics that create distance to services and inequitable facility distribution increases vulnerability regardless of preparation time, thus these groups experience greater hardship. Store visitation in the preparation stage of the disasters is an indicator of accessibility to essential items for hurricane preparation. Visiting more stores does not necessarily indicate greater preparation; rather, it could indicate greater difficulty in obtaining to critical supplies. If low-income households visit only one store during the pre-disaster preparation period, being far from their nearest grocery store (more than 14 miles) or lacking awareness of the storm's impact were the strongest indicators of their hardship experienced due to food service disruptions. These areas can be identified for new facility developments, focusing on improving access to facilities in those affected areas. Mitigation strategies and solutions may include opening new stores in food desert zones, adjusting store hours and store capacity to serve customers with special needs or from high-risk areas, and setting limitations on the purchase of essential items at peak preparation times

Improve relief resource allocation (food, power generators, water) and shelter location selection.

Humanitarian and disaster relief organizations already participate in supply stockpiling or pre-positioning of critical relief supplies in strategic locations (Balcik & Beamon, 2008) so that supplies can be mobilized and delivered quickly (Balcik & Beamon, 2008). However, it remains a challenge to set up effective and efficient networks for supply distribution (Balcik & Beamon, 2008) due to expenses and complexity (Marianov & ReVelle, 1995; ReVelle, Bigman, Schilling, Cohon, & Church, 1977). Commonly used distribution facility location models focus on user accessibility and response time to determine the optimal geographical locations for facilities (Balcik & Beamon, 2008). However, these models focus on locations that reach the greatest populations, but not necessarily those who are most impacted. The pathways identified in this study can help improve the relief and supply distribution process by indicating who and where accessibility improvements can be made within a community. Relief agencies can prioritize areas to ensure critical services and supplies (food, water, power generators) and temporary shelters are provided to households before disasters strike.

Improve the monitoring of preparedness behaviors in susceptible population groups before hurricanes and communication of risks to encourage effective preparation.

Based on the study findings, preparedness actions become significant in a pathway only in the presence of other factors. For example, in the case of water service disruptions, if a household experienced fewer than eight days of disruption, hardship can only be reduced if the household three or fewer occupants. Furthermore, some hardship-mitigating factors are not consistent across infrastructure services nor across segment group population. For an example, for high-income households, having prior disaster damage experience led to less hardship due to water disruptions compared to a high-income household that did not have prior experience with damages during a disaster. Conversely, for low-income households experiencing power disruptions, having prior experience with disaster damages did not appear to mitigate the extent of hardship experienced. In fact, a reverse relationship occurred.

A poor mitigation strategy would be to communicate to households to be prepared well-in-advance for disasters. This ignores the fact that some households face various physical barriers related to the lack of sufficient infrastructure services and social barriers to sufficient preparation. Furthermore, overpreparation could be potentially counterproductive in achieving disaster resiliency (Thompson, Holman, & Silver, 2019), on the basis that having more time to think about the disaster would only give them more time to worry. Pre-emptive actions can lead to the wrong people preparing, absorbing critical resources and services that susceptible households need (Meyer, 2019).

There are several points of intervention where stakeholders can take the lead to help households be more resilient in face of disasters at a household level by improving and easing the preparation process. Some pathways in the analysis were governed more by factors that require household-level interventions. Improving risk communication of service outages and other outstanding threats and improving the awareness of disaster risks through better educational outreach programs in communities, focusing specifically on high-risk individuals and households can mitigate risk. Risk communication can be improved to alert susceptible households to disaster and disruption hazards to encourage preparation actions and behaviors. For example, crowd-sourced data can be used to help close communication gaps. Having multiple ways to be notified in case one method fails is another critical household-level approach to ensure up-to-date and accurate situational awareness during disruptive events (Cappucci, 2020).

By monitoring the visits to points of interest like grocery stores and patterns of preparedness, stakeholders can better monitor inherent susceptibility in the community. Monitoring preparation can be done by tracking visits to points of interests (POIs) ahead of storms (Podesta et al., 2021). Areas that do not indicate high levels of movement to certain points of interest can indicate low preparedness, and consequently, areas of high vulnerability to certain service disruptions. Stakeholders can use this information to identify high risk areas that will need service-restoration first. Similarly, local stakeholders can use this indication of preparedness to understand the inherent susceptibility of households in their community.

CONCLUDING REMARKS

Infrastructure resilience approaches need to recognize human-centric aspects related to different ways subpopulations are impacted during service disruptions. The pathways identified in this study highlight what types of household-level interventions are needed in addition to infrastructure-level interventions, and a combination of both, by addressing factors of inherent susceptibility, protective actions, and reducing hazard exposures. Furthermore, the approach to human-centric infrastructure resilience emphasizes safe-to-fail approaches as opposed to failsafe. A safe-to-fail approach should ensure minimizing hardships due to service disruptions in an equitable manner. In a human-centric resilience approach, while physical improvements in infrastructure systems are a critical component of resilience, interventions at the household level are equally important. Household-level interventions focus on improving the capabilities of households to withstand service disruptions and mitigate their overall hardship experience.

This study presented novel empirical insights for identifying the unique combination of factors that lead to hardship outcomes in households due to infrastructure service disruptions. The results of the pathway analysis highlight the presence of heterogeneous pathways to hardship among households due to infrastructure disruptions. Hardship experiences due to service disruptions are not heterogeneous and depend on the inherent susceptibility of households to service disruptions, their protective actions, and exposure to environmental hazards and risks in their communities. The pathways demonstrated points of intervention to mitigate hardship experience at both the household and infrastructure management stakeholder levels. The pathways help identify where stakeholders can step in to help improve protective action uptake, or where community leaders need to step in to make improvements.

The findings from this study address an important gap in the literature related to the understanding the pathways that connect infrastructure service disruptions to household-level impacts and provide empirical insights regarding why different sub-populations experience disparate impacts during service outages. In particular, the finding related to the existence of multiple pathways to hardship for each sub-population rejects a common belief that improving infrastructure resilience could be achieve by some one-size-fits-all approaches. Accordingly, the study and findings contribute to advancing the theory of human-centric infrastructure resilience. From a practical perspective, the findings offer new insights for infrastructure managers and operators, as well as for emergency managers regarding strategies to reduce the societal impacts and disparities caused by infrastructure service disruptions in disasters.

While this study has specified the important combination of factors that contribute to disparate hardship outcomes due to different service disruptions and by different population segments, future work will need to be done in the area of prioritizing mitigation strategies. The prioritization of mitigation strategies may translate to selecting interventions that would strike a balance between impact and equity. The pathways developed by the pathway models visualize the complexity of hardship pathways as they relate to specific infrastructure systems and population groups. The results of this analysis further emphasize the need for human-centric infrastructure resilience strategies, as well as for population-specific interventions for mitigating the extent of hardship experienced due to service disruptions during hurricanes and other natural hazards. Flexible methods focusing on a wide range of resilience characteristics should be used to identify high-risk households and to inform more resilient and human-centric policies and programs that can address insufficiencies.

ACKNOWLEDGMENTS

The authors would like to acknowledge funding support from the National Science Foundation under grant number 1846069. Any opinions, findings, conclusion, or recommendations expressed in this research are those of the authors and do not necessarily reflect the view of the funding agencies.

CHAPTER VI: CONCLUSION

OVERVIEW

This research has strived to address the core challenges in the nexus of humans, disasters, and the built environment using theory from infrastructure system resilience, social science, public health, and disaster science. A core component of this research is the use of Data Science and Statistical Learning approaches to address existing gaps in our understanding of the relationships between households and critical infrastructure systems in the context of crises. I proposed a methodology that integrates statistical modeling and computational social science to identify the underlying mechanisms and triggers of household-level disaster-impact disparities resulting from critical infrastructure service disruptions. I developed a human-centric disaster resilience model that integrates empirical survey data and digital trace data (i.e., social media and human mobility data) to understand the differential impacts of infrastructure service disruptions (i.e., water, electricity, transportation) on vulnerable population groups in urban areas. The modeling development and output aimed to highlight the inequities in disaster vulnerability and impact and the unique hardship pathways as a result of different levels of protective actions, inherent susceptibility, and hazard exposures. The contributions of my research have several applications to the broader disaster community and beyond, yielding insights into the dynamics of communities in crises, and in parallel, informing interventions and protocols that ensure the well-being and safety of households.

This research aimed to assess the interactions between households and infrastructure service systems to deepen the empirical and theoretical knowledge of the underlying dynamics that influence risk disparities in vulnerable population groups due to infrastructure service gaps during disasters. A substantial focus in particular, the research aimed to empirically assess the extent to which different social subpopulation groups are impacted by service disruptions differently through: (1) exposure to disasters, (2) well-being assessments, and (3) pre-existing household characteristics and conditions. The four studies presented in this dissertation each contribute to a data-driven and human-centric understanding of household-level infrastructure service disruption disparities during natural hazards. Secondly, the studies identify the differential factors of disruption risk impact (digital divide, protective actions, household characteristics)) of differential disruption impacts in affected households). The specific theoretical and practical contributions of each study are presented in the sections below. Future work along the path of these studies is proposed.

KEY FINDINGS

The research presented in this dissertation makes significant theoretical contributions to the area of human-centric infrastructure resilience by developing a human-centric approach for understanding household-infrastructure systems during disasters. To my knowledge, this research provides the first systemic study of addressing the relationships between well-being and hardship of households and infrastructure service disruptions in online space. The results of the experiments empirically verified that well-being is a significant factor in determining how service disruptions impact households differently and how factors of this disparity depend on the complexity and integration of social systems, protective actions, and hazard exposure before and after disasters.

In Chapter 2, the characterization of subjective well-being is used to explain to what extent infrastructure service disruptions influence different subpopulations. The results show that: (1) disruptions in transportation, solid waste, food, and water infrastructure services resulted in more significant well-being impact disparities as compared to electricity and communication services;

(2) households identifying as Black and African American experienced well-being impact due to disruptions in food, transportation, and solid waste services; and (3) households were more likely to feel helpless, difficulty doing daily tasks and feeling distance from their community as a result of service disruptions.

In Chapter 3, it was found that socioeconomic factors along with geographic effects play a role in determining not only platform uptake but both motivations for information seeking and the action of information sharing on social media, (2) The type of social media platform influences the type of information people seek. Households from lower socioeconomic and minority backgrounds were more likely to seek out different information on social media from their peers. Perceptions of information reliability are also influenced by social divides, where households in rural areas, lower income groups, and racial minorities were more likely to report greater unreliability in social media information.

In Chapter 4, The pre-existing conditions of communities in terms of its physical attributes, preparation behaviors, and the coupled durations of FEW infrastructure disruptions were each found to have statistically significant associations with heightened household vulnerability to FEW service disruptions. Physical and prior experience with disasters were found to be the most significant indicators of poor preparation behavior. households with children, racial minority status, and low income and educational attainment of households were associated with having lower levels of preparedness.

In Chapter 5, the results reveal how the associative pathways between these factors change concerning different socioeconomic and demographic groups in the impacted community and different infrastructure service system types. It was found that Inherent Susceptibility, Protective Action, and Risk Exposure related factors and their relative importance vary across different subpopulation groups and different infrastructure services. Additionally, the effect of factors in their respective hardship pathways depends on the presence or absence of other factors. Lastly, the hardship pathways provide recommendations for improving resilience in infrastructure systems in a more equitable manner.

THEORETICAL AND PRACTICAL CONTRIBUTIONS

Enhancing the resilience of infrastructure service systems through planning, mitigation efforts, and rapid response protocols are the fundamental steps infrastructure management stakeholders need to take to enhance the resilience of infrastructure systems in face of future natural disasters. Being able to systematically capture the differential experiences of sub-populations in a community due to infrastructure disruptions is necessary for highlighting the differential needs and inequities that households have. The studies presented in this dissertation collectively contribute empirical knowledge and understanding of household-level infrastructure system interactions during disasters. The studies each aimed to quantify the social impacts of service disruptions through human-centric measures such as well-being and hardship experiences. In Study 1, I was able to establish, through an in-depth correlation analysis, that well-being can be used as a robust social measure of infrastructure resilience. The results of Study 1 established that well-being and infrastructure service disruptions are correlated and that the extent of well-being impact and the type of well-being (i.e., anxiety, safety, connectedness) depends on a combination of sociodemographic characteristics and the type of service outage (i.e., water versus power). There is now usable and empirically based knowledge that shows that the social repercussions of service disruptions are different for different types of households. In Study 2, additional strives to establish an empirical understanding of the differential impacts of service disruptions on households was looked at through the lens of information sharing behaviors on social media platforms. The empirical information contributed to infrastructure resilience theory is that the digital divide on social media platforms (related to social vulnerability factors) during disasters has negative implications on the extent to which households experience hardship due to infrastructure service disruptions. From the perspective of a utility manager and relevant stakeholders, this new information can be used to develop mitigation strategies that are centric to the unique needs of the households in their service area. Understanding wellbeing impact from an infrastructure perspective can help utility managers and operators identify areas that will experience significant hardship and prioritize those areas for service restorations during and after disasters.

Studies 3 and 4 establish the empirical relationships across household and social systems with infrastructure systems during disasters. In Study 3, I developed a framework that integrated Food-Energy-Water Nexus thinking with infrastructure and disaster resilience concepts. The development of this novel framework established empirically the bi-directional relationships between FEW systems, the built-environment, existing social systems, and households during disasters. The use of Structural Equation Models in this study confirmed the roles of various disaster risk measures and the existing social and physical infrastructure systems of a community in compounding household-level vulnerability to disruption impacts. In Study 4, Classification and Regression Trees (CART) models established that hardship mitigation strategies for reducing the impact disparity gap will be specific not only to the population group affected but the type of infrastructure service. The pathways identified from the resulting models can help determine appropriate infrastructure-level or household level intervention gradients for improving the resiliency of household-infrastructure service system interactions. The results demonstrate that within the pathways to hardship outcomes in households, there are certain points of intervention that should be prioritized by stakeholders to improve the overall household-level resilience service disruptions. For example, prioritizing the awareness and accessibility to protective actions can help households prepare for disruptions in Food and Transportation services and bolster the resilience of households against future disruptions.

Collectively, the four studies contribute to different levels of empirical knowledge of household-infrastructure interactions during disasters. With the acknowledgement that infrastructure systems cannot be made failsafe, it's important for disaster managers and infrastructure owner operators to be aware of the inherent susceptibilities that exist in their service population exist, so they know which areas are more likely to be susceptible to disruption impacts. In many situations, this equates to ensuring equitable access to stores selling essential supplies. Mitigation strategies and solutions may look like opening new stores in food desert zones, adjusting store hours and store capacity to serve customers with special needs or from high-risk areas, and setting limitations on the purchase of essential items at peak preparation times. Monitoring preparation can be done by tracking visits to points of interests (POIs) ahead of storms (Podesta, Coleman, Esmalian, Yuan, & Mostafavi, 2021). Areas that do not indicate high levels of movement to certain points of interests can indicate low preparedness, and consequently, areas of high vulnerability to certain service disruptions. Stakeholders can use this information to identify high risk areas that will need service-restoration first. Similarly, local stakeholders can use this indication of preparedness to understand the inherent susceptibility of households in their community.

RECOMMENDATIONS FOR FUTURE WORK

The research in this dissertation has provided the necessary empirical foundation of knowledge and evidence for understanding the social inequities in infrastructure service disruptions in households.

Causal Analysis of Pathways and Policy Development

The underlying factors of hardship disparities in households were identified for different service disruptions. Further analysis would focus on identifying the existing structures and systems with communities that cause these factors of disparity to exist in the first place. There is not a one size fits all solution to infrastructure resilience problems, which is why integrating human-centric measures into resilience studies and assessments is so critical. So given that there is not one solution, the challenge is developing strategies and policies that fit local and community needs. This is not addressed in the research of my dissertation work. My research lays the empirical groundwork that answers why and where disparities exist, who suffers and how much. Building from this work, further research is needed to understand how to develop human-centric strategies that meet all the requirements and the special needs of the population groups, and how this improves the resiliency of infrastructure and communities against disasters overtime. Case studies can be developed to guide stakeholders in prioritizing this information to develop interventions that like balance between impact and ensuring that it's serving the community.

Integrating Findings into Equitable AI Modeling

Data communicated through various mediums such as social media, smartphone apps, and sensors during disasters contain useful insights into not just the spatial and temporal characteristics of a disaster's impacts, but also their magnitude and criticality, as well as people's protective action behaviors. However, this data only represents a fraction of the population and not necessarily those with greater exposures to hazards and impacts of disasters. Concurrently, existing social media algorithms could be biased against vulnerable populations. A disparity in platform activity may actually compound social inequalities as opposed to alleviating them. With these inherent bias and fairness problems related to data and algorithms in crisis informatics, it is critical to reconsider the ground-truth of research by fusing data from various sources across different disasters.

Findings from the research in this dissertation can be used to guide the development of algorithms and data processing techniques to ensure equitable and fair models that yield insights into the dynamics of communities in crisis situations, and in parallel, inform interventions and protocols that ensure the well-being and safety of communities. Further research is needed in this area to understand how digital trace highlights the inequalities in at-risk populations during disasters and crisis situations. More specifically, how interactions between a community's population and its built environment might suppress or amplify hazard exposure and its effects. Further research can be done to improve the digital literacy of vulnerable populations by employing social media to augment their response capacity during disasters and sense emotional signals from social media to examine wellbeing impacts on vulnerable populations during crisis.

REFERENCES

A. Ahmed, J. Sargent, Analysis of post-crisis twitter communication: a study of the Iquique Chile earthquake, in: 25th Australasian Conference on Information Systems, 2014 (Auckland, NZ).

A. Ahmed, J. Sinnappan, The role of social media during Queensland Floods: an empirical investigation on the existence of multiple communities of practice (MCoPs), Pac. Asia J. Assoc. Inf. Syst. 5 (2013) 2.

A. Grand, Social networks and popular understanding of science and health: Sharing disparities, Journal of Science Communication 13 (2014), https://doi. org/10.22323/2.13040701.

A. Mislove, S. Lehmann, Y.Y. Ahn, J.P. Onnela, J.N. Rosenquist, Understanding the demographics of Twitter users, in: Fifth International AAAI Conference on Weblogs and Social Media, 2011, July.

A. Olteanu, C. Castillo, F. Diaz, E. Kiciman, Social data: biases, methodological pitfalls, and ethical boundaries, Front. Big Data 2 (2019) 13, https://doi.org/10.3389/fdata.2019.00013.

A. Perrin, Digital Gap between Rural and Nonrual America Persists. FACTANK: News in the Numbers; PEW Research Center, 2019 https://www.pewresearch. org/fact-tank/2019/05/31/digital-gap-between-rural-and-nonrural-america- persists/.

A.K. Chatfield, H.J. Scholl, U. Brajawidagda, Tsunami early warnings via Twitter in government: net-savvy citizens' co-production of time-critical public information services, Govern. Inf. Q. 30 (4) (2013) 377–386, https://doi.org/ 10.1016/j.giq.2013.05.021.

A.K.B.U. Chatfield, Twitter tsunami early warning network: a social network analysis of Twitter information flows. ACIS 2012: location, location, location, in: Proceedings of the 23rd Australasian Conference on Information Systems 2012, 2012, p. 10.

A.L. Hughes, L.A.A.S. Denis, L. Palen, K.M. Anderson, Online public communications by police & fire services during the 2012 Hurricane Sandy, in: Paper Presented at the Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Canada, Toronto, Ontario, 2014 https://doi.org/10.1145/ 2556288.2557227.

A.W. Blume, Social Issues in Living Color: Challenges and Solutions from the Perspective of Ethnic Minority Psychology, Praeger; An Imprint of ABC-CLIO, LLC, Santa Barbara, California, 2017.

Ablah, E., Konda, K., & Kelley, C. L. (2009). Factors predicting individual emergency preparedness: a multi-state analysis of the 2006 BRFSS data. *Biosecur Bioterror, 7*, 317–330.

Ackerson, L. K., & Viswanath, K. (2009). The Social Context of Interpersonal Communication and Health. *Journal of Health Communication, 14*(sup1), 5-17. doi:10.1080/10810730902806836.

Adam Acar, Yuya Muraki, Twitter for crisis communication: lessons learned from Japan's tsunami disaster, IJWBC 7 (2011) 392–402, https://doi.org/10.1504/ IJWBC.2011.041206.

Adelman, M., Ivaschenko, O., Packard, T. G., & Suri, V. (2015). Hardship and vulnerability in the Pacific island countries (English). *Washington, D.C*http://documents. worldbank.org/curated/en/649891468098658407/Hardship-and-vulnerability-in- the-Pacific-island-countries.

Adeola, F.O. Flood hazard vulnerability: A study of Tropical Storm Allison (TSA) flood impacts and adaptation modes in Louisiana (Quick Response Research Report #162). 2003; Boulder, CO: Natural hazards Research & Application Center, University of Colorado. Retrieved from http://www.colorado. edu/hazards/research/qr/qr162/qr162.html.

Ahn, J. The effect of social network sites on adolescents' social and academic development: Current theories and controversies, Journal of the American Society for Information Science and Technology 62 (8) (2011) 1435–1445, https://doi. org/10.1002/asi.21540.

Aitsi-Selmi A., Egawa S., Sasaki H., Wannous C., Murray V. The Sendai framework for disaster risk reduction: Renewing the global commitment to people's resilience, health, and well-being. Int. J. Disaster Risk Sci. 2015, 6, 164–176. https://doi.org/10.1007/s13753-015-0050-9

Akoglu H. User's guide to correlation coefficients. Turk J Emergency Med. 2018; 18(3):91–3. https://doi. org/10.1016/j.tjem.2018.08.001

Alderson D.L, Carlyle W.M. Operational Models of Infrastructure Resilience. Risk Analysis. 2015; 35 (4).

Alexander, D. (2012). Models of social vulnerability to disasters. *RCCS Annual Review*. https://doi.org/10.4000/rccsar.412.

Andrulis D.P., Siddiqui N.J, Purtle J.P. Integrating Racially and Ethnically Diverse Communities Into Planning for Disasters: The California Experience. Disaster Medicine and Public Health Preparedness. 2011; 5(3):227–34.

Apostolakis, G. E., & Lemon, D. M. (2005). A screening methodology for the identification and ranking of infrastructure vulnerabilities due to terrorism. *Risk Analysis*, *25*(2), 361–376.

Assessments for Natural Disasters Reduction. In J. Tiefenbacher (Ed.). *Approaches to Disaster Management—Examining the Implications of Hazards*. InTech: Emergencies and Disasters.

B. Ripley, W. Venables, Package "Nnet", 2016 (https://cran.r-project.org/web/packages/nnet/index.html).

Badland H., Whitzman C., Lowe M., Davern M., Aye L., Butterworth I., et al. Urban livability: Emerging lessons from Australia for exploring the potential for indicators to measure the social determinants of health. Social Science & Medicine. 2014; 111:64–73. https://doi.org/10.1016/j.socscimed.2014.04

Baggio S, Colliard C. Tsunami et bien-être subjectif: effet de l'implication personnelle et de la sociabi- lite´ . Cahiers Internationaux de Psychologie Sociale. 2007; 74:19–28. https://doi.org/10.3917/cips.074. 0019

Baker, J. L. (2012). *Climate change, disaster risk, and the urban poor.* The World Bank.

Balaei, B., Wilkinson, S., Potangaroa, R., & McFarlane, P. (2020). Investigating the technical dimension of water supply resilience to disasters. *Sustainable Cities and Society.56.*. https://doi.org/10.1016/j.scs.2020.102077.

Barrett C., Channakeshava K., Huang F., Kim J., Marathe A., Marathe M.V., et al. Human Initiated Cascading Failures in Societal Infrastructures. PLOS ONE. 2012; 7(10): e45406. https://doi.org/10. 1371/journal.pone.0045406

Basolo, V., Steinberg, L. J., Burby, R. J., Levine, J., Cruz, A. M., & Huang, C. (2009). The effects of confidence in government and information on perceived and actual preparedness for disasters. *Environment and Behavior, 41*(3), 338–364. https://doi.org/10.1177/0013916508317222.

Batouli, M., & Mostafavi, A. (2018). Multi-agent simulation for complex adaptive modeling of roadway infrastructure resilience to sea-level rise. *Journal of Computer-Aided Civil and Infrastructure Engineering, 33*(5), 17.

Becker, D. Paton, D.M. Johnston, K.R. Ronan, J. McClure, The role of prior experience in informing and motivating earthquake preparedness, Int. J. Disas. Risk Reduction. 22 (2017) 179–193, https://doi.org/10.1016/j.ijdrr.2017.03.006.

Becker, J. S., Paton, D., Johnston, D. M., Ronan, K. R., & McClure, J. (2017). The role of prior experience in informing and motivating earthquake preparedness. *International Journal of Disaster Risk Reduction, 22*, 179–193. https://doi.org/10.1016/j.ijdrr.2017. 03.006.

Bergstrand, K., Mayer, B., Brumback, & Zhang, B. (2014). Assessing the Relationship Between Social Vulnerability and Community Resilience to Hazards. *Social Indicators Research, 122*. https://doi.org/10.1007/s11205-014-0698-3.

Blank, G., Lutz, C. Representativeness of Social Media in Great Britain: Investigating Facebook, LinkedIn, Twitter, Pinterest, Google+, and Instagram, American Behavioral Scientist 61 (7) (2017) 741–756, https://doi.org/10.1177/ 000276421771755

Blumenfeld, L., Hall, T., Henderson, H., Bressler, L., Moskos, C., Bhatia, U., & Ganguly, A. R. (2017). Climate and human stresses on the Water-energy-food nexus. In S. Shekhar, H. Xiong, & X. Zhou (Eds.). *Encyclopedia of GIS* (pp. 179–188). Cham: Springer International Publishing.

Blunt, K. Harvey floodwaters left some neighborhoods in food desert. Houston Chronicle. 2017. Retrieved from: https://www.houstonchronicle.com/business/retail/article/In-some-communities- Harvey-left-a-food-desert-12178637.php

Boehm J.K., Kubzansky L.D. The Heart's Content: The Association between Positive Psychological Well-Being and Cardiovascular Health. Psychological Bulletin. 2012; 138(4):655–691. https://doi.org/ 10.1037/a0027448

Brian Smith, Linjuan Men, Reham Al-Sinan, Tweeting Taksim communication power and social media advocacy in the Taksim square protests, Comput. Hum. Behav. 50 (2015), https://doi.org/10.1016/j.chb.2015.04.012.

Brown C., Milke M., Seville E. Disaster waste management: A review article. Waste Management. 2011; 31(6):1085–98. https://doi.org/10.1016/j.wasman.2011.01.027

Brown K., Westaway E. Agency, Capacity, and Resilience to Environmental Change: Lessons from Human Development, Well-Being, and Disasters. Annual Review of Environment and Resources. 2011; 36(1):321–42.

Bruneau M., Chang S.E., Eguchi R.T., Lee G.C., O'Rourke T.D., Reinhorn A.M., et al. A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. Earthquake Spectra. 2003; 19(4): 733–52. https://doi.org/10.1193/1.1623497

Bubenik T. Though power outages were limited, Harvey revealed new challenges for the grid. Houston Public Media, Energy and Environment. 2017. Retrieved from: https://www.houstonpublicmedia.org/ articles/news/energy-environment/2017/11/02/248175/though-power-outages-were-limited-harvey- revealed-new-challenges-for-the-grid/.

Buckle, Philip; Mars, Graham; Smale, S. (2000). "New approaches to assessing vulnerability and resilience." *Australian Journal of Emergency Management*, 15(2).

Burrus R.T, Dumas C.F, Farrell C.H, Hall W.W. Impact of Low-Intensity Hurricanes on Regional Economic Activity. Natural Hazards Review. 2002; 3(3):118–25.

C. Castillo, Big Crisis Data: Social Media in Disasters and Time-Critical Situations, Cambridge University Press, 2016.

C. Chen, P. Ractham, L. Kaewkitipong, The community-based model of using social media to share knowledge to combat crises, PACIS 2014 Proceed. 387 (2014) 2014, https://jcom.sissa.it/archive/13/04/JCOM_1304_2014_R01.

C. Reuter, A.L. Hughes, M.-A. Kaufhold, Social media in crisis management: an evaluation and analysis of crisis informatics research, Int. J. Hum. Comput. Interact. 34 (4) (2019) 280–294, https://doi.org/10.1080/ 10447318.2018.1427832.

C. Tang, X. Wu, X. Chen, B. Pan, X. Yang, Examining income-related inequality in health literacy and health-information seeking among urban population in China, BMC Publ. Health 19 (1) (2019) 221, https://doi.org/10.1186/s12889-019-6538- 2.

C. Zhang, C. Fan, W. Yao, X. Hu, A. Mostafavi, Social media for intelligent public information and warning in disasters: an interdisciplinary review, Int. J. Inf. Management. 49 (2019) 190–207, https://doi.org/10.1016/j.ijinfomgt.2019.04.004.

C.C. Kuhlthau, Inside the search process: information seeking from the user's perspective, J. Am. Soc. Inf. Sci. 42 (5) (1991) 361–371, 10.1002/(sici)1097-4571(199106)42:5<361::Aid-asi6>3.0.Co;2-#.

Capic T., Cummins R.A., Silins E., Richardson B., Fuller-Tyszkiewicz M. Australian Unity Wellbeing Index Survey 33.0: Part A: The Wellbeing of Australians: Federal Electoral Divisions, Homeostatically Protected Mood and Relationship Support. 2016: Melbourne: Deakin.

Cariolet, J. M., Vuillet, M., & Diab, Y. (2019). Mapping urban resilience to disasters – A review. *Sustainable Cities and Society, 51*, Article 101746. https://doi.org/10.1016/j. scs.2019.101746 ISSN 2210-6707.

Center for Disease Control and Prevention (CDC). Well-being Concepts. National Center for Chronic Disease Prevention and Health Promotion, Division of Population Health. 2018. https://www.cdc.gov/ hrqol/wellbeing.htm.

Chakalian, P. M., Kurtz, L. C., and Hondula, D. M. (2019). "After the Lights Go Out: Household Resilience to Electrical Grid Failure Following Hurricane Irma." *Natural Hazards Review*, 20(4), 05019001.

Chang S.E. Socioeconomic Impacts of Infrastructure Disruptions. Oxford University Press; 2016. https://doi.org/10.1093/acrefore/9780199389407.013.6

Chang, S. E., McDaniels, T., Fox, J., Dhariwal, R., & Longstaff, H. (2014). Toward disaster-resilient cities: Characterizing resilience of infrastructure systems with expert judg ments. *Risk Analysis, 34,* 416–434. https://doi.org/10.1111/risa.12133.

Ciurean, R. L., Schroter, D., & Glade, T. (2013). Conceptual Frameworks of Vulnerability

Cleland C., Kearns A., Tannahill C., Ellaway A. The impact of life events on adult physical and mental health and well-being: longitudinal analysis using the GoWell health and well-being survey. BMC Research Notes. 2016; 9(1):470. BMC Res Notes. 2016; 9: 470. https://doi.org/10.1186/s13104-016- 2278-x

Coleman, N., Esmalian, A., and Mostafavi, A. (2019). “Equitable Resilience in Infrastructure Systems: Empirical Assessment of Disparities in Hardship Experiences of Vulnerable Populations during Service Disruptions.” *Natural Hazards Review*.

Cui, P., & Li, D. (2020). A SNA-based methodology for measuring the community resilience from the perspective of social capitals: Take Nanjing, China as an example. *Sustainable Cities and Society, 53*. https://doi.org/10.1016/j.scs.2019.101880.

Czaja S.J., Charness N., Fisk A.D., Hertzog C., Nair S.N., Rogers W.A., et al. Factors predicting the use of technology: findings from the Center for Research and Education on Aging and Technology Enhancement (CREATE). Psychol Aging. 2006; 21(2):333–52. https://doi.org/10.1037/0882-7974.21. 2.333 PMID: 16768579

D. Constant, S. Kiesler, L. Sproull, What’s mine is ours, or is it? A study of attitudes about information sharing, Inf. Syst. Res. 5 (4) (1994) 400–421, https:// doi.org/10.1287/isre.5.4.400.

D. Ruths, J. Pfeffer, Social media for large studies of behavior, Science 346 (6213) (2014) 1063, https://doi.org/10.1126/science.346.6213.1063.

D. Sterrett, D. Malato, J. Benz, L. Kantor, T. Tompson, T. Rosenstiel, K. Loker, Who shared it?: deciding what news to trust on social media, Digital J. 7 (6) (2019) 783–801, https://doi.org/10.1080/21670811.2019.162370.

D.L. Bird, Megan, Katharine Haynes, Flooding Facebook? The use of social media during the Queensland and Victorian floods, Aust. J. Emerg. Management. 27 (2012).

D.M. Tootle, Disaster recovery in rural communities: a case study of southwest Louisiana, South. Rural Sociol. 22 (2007) 21.

Daher, B. T., & Mohtar, R. H. (2015). Water–Energy–Food (WEF) Nexus tool 2.0: Guiding integrative resource planning and decision-making. *Water International, 40*(5-6), 748–771. https://doi.org/10.1080/02508060.2015.1074148.

Dargin, J. S., & Mostafavi, A. (2020). Human-centric infrastructure resilience: Uncovering well-being risk disparity due to infrastructure disruptions in disasters. *PLOS ONE, 15*(6), https://doi.org/10.1371/journal.pone.0234381 e0234381.

Davis, C., Mostafavi, A., & Wang, H. (2018). Establishing characteristics to operationalize resilience for lifeline systems. *ASCE Natural Hazards Review, 19*(4).

de Albuquerque, JP, Herfort, B., Brenning, A., Zipf, A geographic approach for combining social media and authoritative data towards identifying useful information for disaster management, Int. J. Geography. Inf. Sci. 29 (4) (2015) 667–689, https://doi.org/10.1080/13658816.2014.996567.

Diedenhofen B., Musch J. cocor: A Comprehensive Solution for the Statistical Comparison of Correlations. PLOS ONE. 2015; 10(4):e0121945.

Diener E., Biswas-Diener. Will Money Increase Subjective Well-Being? Social Indicators Research. 2002; 57: 119. https://doi.org/10.1023/A:1014411319119

Dong, S., Esmalian, A., Farahmand, H., & Mostafavi, A. (2019). An integrated physical- social analysis of disrupted access to critical facilities and community service-loss tolerance in urban flooding. *Computers, Environment and Urban Systems Journal*.

Dong, S., Wang, H., Mostafavi, A., & Gao, J. (2019). Impact of post-disaster network access to critical facilities on network robustness. *Journal of the Royal Society, Interface*. https://doi.org/10.1098/rsif.2019.0149.

Doorn N., Gardoni P., Murphy C. A multidisciplinary definition and evaluation of resilience: the role of social justice in defining resilience. Sustainable and Resilient Infrastructure. 2018:1–12.

Duggan, M., Ellison, N., Lampe, C., Lenhart, A., Madden, M. (2015). Social media update 2014: While Facebook remains the most popular site, other platforms see higher rates of growth. Pew Research Center. Retrieved from http://www.pewinternet.org/files/2015/01/PI_SocialMediaUpdate20141.pdf.

E. Hargittai, Second-Level Digital Divide: Differences in People's Online Skills, vol. 7, First Monday, 2002. Retrieved from http://firstmonday.org/issues/issue7_ 4/hargittai/index.html.

E. Hargittai, Whose space? Differences among users and non-users of social network sites, J. Computer-Mediated Communications. 13 (1) (2007) 276–297, https:// doi.org/10.1111/j.1083-6101.2007.00396.x.

E.S. Blake, D.A. Zelinsky, National Hurricane Center Tropical Cyclone Report, 2017. Retrieved from https://www.nhc.noaa.gov/data/tcr/AL092017_Harvey. pdf.

E.Z. Kontos, K.M. Emmons, E. Puleo, K. Viswanath, Communication inequalities and public health implications of adult social networking site use in the United States, J. Health Commun. 15 Suppl 3 (Suppl 3) (2010) 216–235, https://doi.org/ 10.1080/10810730.2010.522689.

Earl, J. CITASA: intellectual past and future, Inf. Communities. Soc. 18 (5) (2015) 478–491, https://doi.org/10.1080/1369118X.2015.1008544.

Eisenman, D. P., Zhou, Q., Ong, M., Asch, S., Glik, D., & Long, A. (2009). Variations in disaster preparedness by mental health, perceived general health, and disability status. *Disaster Medicine and Public Health Preparedness*, *3*(1), 33–41. https://doi.org/ 10.1097/DMP.0b013e318193be89.

Endo, A., Burnett, K., Orencio, P., Kumazawa, T., Wada, C., Ishii, A., ... Tsurita, I., et al. (2015). Methods of the water-energy-Food Nexus. *Water, 7*(10), 24. https://doi.org/10.3390/w7105806.

Esmalian A., Ramaswamy M., Rasoulkhani K. Mostafavi A. (2019). Agent-Based Modeling Frame- work for Simulation of Societal Impacts of Infrastructure Service Disruptions during Disasters. Computing in Civil Engineering 2019. p. 16–23. https://doi.org/10.1061/9780784482445

Esmalian, A., Dong, K., and Mostafavi, A. (2020). "Empirical Assessment of Household Susceptibility to Hazards-induced Prolonged Power Outages." *Construction Research Congress*.

Esmalian, A., Dong, S., Coleman, N., and Mostafavi, A. (2019a). "Determinants of risk disparity due to infrastructure service losses in disasters: a household service gap model." *Risk Analysis*.

Esmalian, A., Ramaswamy, M., Rasoulkhani, K., and Mostafavi, A. (2019b). "Agent-Based Modeling Framework for Simulation of Societal Impacts of Infrastructure Service Disruptions during Disasters." *Computing in Civil Engineering 2019: Smart Cities, Sustainability, and Resilience - Selected Papers from the ASCE International Conference on Computing in Civil Engineering 2019*.

(EPA), E. P. A. (2013). *Providing Safe Drinking Water in America: 2013 National Public Water Systems Compliance Report*Office of Enforcement and Compliance Assurance EPA DOCUMENT 305R15001.

Ewing, R., Tian, G., Goates, J. P., Zhang, M., Greenwald, M. J., Joyce, A., & Greene, W. (2015). Varying influences of the built environment on household travel in 15 diverse regions of the United States. *Urban Studies, 52*(13), 2330–2348.

F. Chao, F. Wu, A. Mostafavi, A Hybrid Machine Learning Pipeline for Automated Mapping of Events and Locations from Social Media in Disasters, IEEE Access, 2020.

F. Shaw, J. Burgess, K. Crawford, A. Bruns, Sharing news, making sense, saying thanks: patterns of talk on Twitter during the Queensland Floods, Aust. J. Commun. 40 (1) (2013) 23–39.

F. Vis, Twitter as a reporting tool for breaking news, Digital Journalism 1 (1) (2013) 27–47.

Facebook. Crisis Response, 2020. Retrieved from: https://www.facebook.com/help/141874516227713/?helpref=hc_fnav.

Falco G.J. City Resilience through Data Analytics: A Human-centric Approach. Procedia Engineering. 2015; 118:1008–14. https://doi.org/10.1016/j.proeng.2015.08.542

Federal Communications Commission (FCC) (2017). Report on the 2017 Atlantic Hurricane Season's Impact on Communications.

FEMA - U.S. Department of Homeland Security (2017). *Power outage incident annex to the response and recovery federal interagency operational plans: Managing the cascading impacts from a long-term power outage.* June. Power Outage Incident Annex. Access:https://www.fema.gov/media-library-data/1512398599047-7565406438d0820111177a9a2d4ee3c6/POIA_Final_7-2017v2_(Compliant_pda)_508.pdf.

Few R., Matthies F. Flood hazards and health: Responding to present and future risks. Flood Hazards and Health: Responding to Present and Future Risks. 2013; 1–219. https://doi.org/10.4324/ 9781849771351

Flanagan B., Gregory E., Hallisey E., Heitgerd J., Lewis B. A Social Vulnerability Index for Disaster Management. Journal of Homeland Security and Emergency Management. 2011; 8(1). https://doi. org/10.2202/1547-7355.1792

Foa E.B., Gillihan S.J., Byrant R.A. "Challenges and Successes in Dissemination of Evidence-Based Treatments for Posttraumatic Stress: Lessons Learned From Prolonged Exposure Therapy for PTSD." Psychological science in the public interest: a journal of the American Psychological Society vol. 14,2 (2013): 65–111. https://doi.org/10.1177/1529100612468841

Fujio Toriumi, Takeshi Sakaki, Kosuke Shinoda, Kazuhiro Kazama, Satoshi Kurihara, Itsuki Noda, Information Sharing on Twitter during the 2011 Catastrophic Earthquake, 2013, pp. 1025–1028, https://doi.org/10.1145/ 2487788.2488110.

G. BrianSouthwell. networks and popular understanding of scienceand health: sharing disparities, Johns Hopkins University Pressand RTIPress, Research, Baltimore Triangle, 2013, p. 106, 13 978-1-4214-1324.

G.C. Kane, M. Alavi, G. Labianca, S.P. Borgatti, What's different about social media networks? A framework and research agenda, MIS Q. 38 (2014) 29.

G.H. Bressler, M.E. Jennex, E.G. Frost, Exercise 24: using social media for crisis response, Proceed. Int. J. Info. Syst. Crisis Res. Management. 3 (4) (2012) 36–54, https://doi.org/10.4018/jiscrm.2011100103.

Gamble, J. L., Hurley, B. J., Schultz, P. A., Jaglom, W. S., Krishnan, N., and Harris, M. (2013). "Climate change and older Americans: state of the science." *Environ Health Perspect*, 121(1), 15–22.

Gao, H., Barbier, G., Goolsby,R. Harnessing the crowdsourcing power of social media for disaster relief, IEEE Intell. Syst. 26 (3) (2011) 10–14, https://doi.org/ 10.1109/MIS.2011.52.

Gray, W., and R. Shadbegian. 2010. When Do Firms Shift Production Across States to Avoid Environmental Regulation? U.S E.P.A. National Center for Environmental Economics mimeo.

Guan X., Chen C., Work D. Tracking the Evolution of Infrastructure Systems and Mass Responses Using Publicly Available Data. PLOS ONE. 2016; 11(12): e0167267.20.

H. Carter, J. Drury, R. Allot, Social identity and intergroup relationships in the management of crowds during mass emergencies and disasters: recommendations for emergency planners and responders, in: Policing: A Journal of Policy and Practice, 2018 https://doi.org/10.1093/police/pay013.

H. Rodriguez, W. Diaz, J. Santos, B.E. Aguirre, Communicating risk and uncertainty: science, technology, and disasters at the crossroads, in: Handbook of Disaster Research, Springer, New York, 2007, pp. 476–488.

Haime, Y. Y., & Jiang, P. (2001). Leontief-based model of risk in complex interconnected infrastructure. *Journal of Infrastructure System*, *7*(1), 1–12.

Haines A., Kovats R.S., Campbell-Lendrum D., Corvalan C. Climate change and human health: impacts, vulnerability, and mitigation. Lancet. 2006 Jun 24; 367(9528):2101–9. https://doi.org/10. 1016/S0140-6736(06)68933-2 PMID: 16798393.

Hajat S., Kovats R.S., Lachowycz K. Heat-related and cold-related deaths in England and Wales: who is at risk? Occupational Environmental Medicine. 2007; 64(2):93–100. https://doi.org/10.1136/oem. 2006.029017

Handy, S. L., Boarnet, M. G., Ewing, R., & Killingsworth, R. E. (2002). How the built environment affects physical activity: Views from urban planning. *American Journal of Preventive Medicine*, *23*(2, Supplement 1), 64–73. https://doi.org/10.1016/S0749-3797(02)00475-0.

Haraguchi, M., & Kim, S. (2016). Critical infrastructure interdependence in New York City during hurricane sandy. *International Journal of Disaster Resilience in the Built Environment*, *7*(2), 10. https://doi.org/10.1108/IJDRBE-03-2015-0015.

Hay A.G-P., Martyn N. Planning Resilient Communities. 2017. In: Resilience and Risk [Internet]. Dordrecht: Springer Science for Peace and Security Series C: Environmental Security.

HCFCD, Impact and Response in Harris County Harris County Flood Control District, 2018 https://www.hcfcd.org/media/3000/hcfcd-harvey-impact-and- response-spreads-final-web-may-2018.pdf.

HCFCD. Impact and Response in Harris County Harris County Flood Control District. 2018. https:// www.hcfcd.org/media/3000/hcfcd-harvey-impact-and-response-spreads-final-web-may-2018.pdf.

Helliwell, J.F, Layard, R., Sachs, J. World happiness report 2013. New York, NY. 2014.

Hersh, R. (1995). *Race and Industrial Hazards: A Historical Geography of the Pittsburgh Region, 1900-*. Discussion Paper 95-18. RFF.

Hinkle W. Applied Statistics for the Behavioral Sciences 5ed. Boston, MA: Houghton Mifflin; 2003. 756 p. ISBN: 978–0618124053.

Hoffmann, R., & Muttarak, R. (2017). Learn from the past, prepare for the future: Impacts of education and experience on disaster preparedness in the Philippines and Thailand. *World Development, 96*, 32–51. https://doi.org/10.1016/j.worlddev.2017. 02.016.

Hussein, W. A., Memon, F. A., & Savic, D. A. (2017). An integrated model to evaluate water-energy-food nexus at a household scale. *Environmental Modelling & Software, 93*, 366–380. https://doi.org/10.1016/j.envsoft.2017.03.034.

Institute of Medicine. Committee on Post-Disaster Recovery of a Community's Public Health, Medical, and Social Services; Board on Health Sciences Policy. Healthy, Resilient, and Sustainable Communities After Disasters: Strategies, Opportunities, and Planning for Recovery. Washington (DC): National Academies Press (US); 2015; Behavioral Health. Available from: https://www.ncbi.nlm.nih.gov/books/ NBK316541/.

Institute of Medicine. Committee on Post-Disaster Recovery of a Community's Public Health, Medical, and Social Services; Board on Health Sciences Policy. Healthy, Resilient, and Sustainable Communities After Disasters: Strategies, Opportunities, and Planning for Recovery. Washington (DC): National Academies Press (US); 2015; Behavioral Health. Available from: https://www.ncbi.nlm.nih.gov/books/ NBK316541/

International Wellbeing Group. Personal Wellbeing Index Manual 5th Edition.(2013) Retrieved from http://www.deakin.edu.au/research/acqol/instruments/wellbeing-index/pwi-a-english.pdf

J. Kim, Mei , M., Hastak, Social network analysis: characteristics of online social networks after a disaster, Int. J. Inf. Management. 38 (2018) 86–96, https://doi.org/ 10.1016/j.ijinfomgt.2017.08.003.

J. Witte, S. Mannon, The Internet and Social Inequalities, Routledge, New York, 2010 https://doi.org/10.4324/9780203861639.

J.B. Houston, M.L. Spialek, J. Cox, et al., The centrality of media and communication in fostering community resilience: a framework for assessment and intervention, Am. Behavior. Sci. 59 (2015) 270–283, https://doi.org/10.1177/ 0002764214548563.

J.H. Park, B. Gu, A.C.M. Leung, P. Konana, An investigation of information sharing and seeking behaviors in online investment communities, Comput. Hum. Behav. 31 (2014) 1–12, https://doi.org/10.1016/j.chb.2013.10.002.

Jones, S., & Fox, S. (2009). Generations Online in 2009. Pew Research Centerhttp://www.pewinternet.org/Reports/2009/Generations-Online-in-2009. aspx.

Joo-Young Jung, Social Media Use and Goals after the Great East Japan Earthquake, vol. 17, First Monday, 2012, https://doi.org/10.5210/fm. v17i8.4071.

Juntunen L. Addressing Social Vulnerability to Hazards. Disaster Safety Review. 2005; 4(2):3–10.

K. Eismann, O. Posegga, K. Fischbach, COLLECTIVE BEHAVIOUR, SOCIAL MEDIA, AND DISASTERS: A SYSTEMATIC LITERATURE REVIEW, in: ECIS 2016 Proceedings, 104. Retrieved from, Association for Information Systems, 2016 http://aisel.aisnet.org/ecis2016_rp/104.

K. Viswanath, Public communications and its role in reducing and eliminating health disparities, in: GE Thomson, F Mitchell, MB Williams (Eds.), Examining the Health Disparities Research Plan of the National Institutes of Health, Unfinished Business. Institute of Medicine, Washington, D.C, 2006, pp. 215–253.

K.A. Borden, S.L. Cutter, Spatial patterns of natural hazards mortality in the United States, Int. J. Health Geogr. 7 (1) (2008) 64, https://doi.org/10.1186/ 1476-072X-7-64.

Kahlke, M. Stability and Sensitivity in Perceived Quality of Life Measures: Some Panel Results. Social Indicators Research. 2010; 98. 403–434. https://doi.org/10.1007/s11205-009-9554-2

Kaufmann, M. Resilience 2.0: social media use and (self-)care during the 2011 Norway attacks, Media, Culture & Society 37 (7) (2015) 972–987, https://doi. org/10.1177/0163443715584101

Kelley J., Evans M.D.R. Societal Inequality and individual subjective well-being: Results from 68 societies and over 200,000 individuals, 1981–2008. Social Science Research. 2017; 62:1–23. https://doi. org/10.1016/j.ssresearch.2016.04.020

Kellezi B, Reicher S, Cassidy C. Surviving the Kosovo Conflict: A Study of Social Identity, Appraisal of Extreme Events, and Mental Well-Being. Applied Psychology. 2008; 58. 59–83. https://doi.org/10.1111/j.1464-0597.2008.00382.x

Keppel KG, Pamuk E, Lynch J, Carter-Pokras O, Kim Insun Mays V, et al. "Methodological issues in measuring health disparities." Vital and health statistics. Series 2, Data evaluation and methods research 141 (2005): 1–16.

Kessler R.C., Nelson C.B., McGonagle K.A., Liu J., Swartz M., Blazer D.G. Comorbidity of DSM–III–R Major Depressive Disorder in the General Population: Results from the US National Comorbidity Sur- vey. British Journal of Psychiatry. 1996; 168(S30):17–30.

Keyes C.L.M.W., Beth M. Dimensions of well-being and mental health in adulthood. 2003. In: Cross- currents in contemporary psychology [Internet]. Mahwah, NJ: Lawrence Erlbaum Associates Publishers; 477–97.

Khumalo I.P., Temane Q.M., Wissing M.P. Socio-Demographic Variables, General Psychological Well-Being and the Mental Health Continuum in an African Context. Social Indicators Research. 2012; 105(3):419–42. https://doi.org/10.1007/s11205-010-9777-2

Kirmayer L, Sedhev WM, Dandeneau, R., Isaac, S. Community Resilience: Models, Metaphors and Measures. Journal of Aboriginal Health. 2009; 5. 62–117.

Kontokosta, C., & Malik, A. (2018). The Resilience to Emergencies and Disasters Index: Applying big data to benchmark and validate neighborhood resilience capacity. *Sustainable Cities and Society, 36*, 272–285. https://doi.org/10.1016/j.scs.2017.10. 025.

Kovats S. Estimating the health burden of current and future extreme events. IOP Conference Series: Earth and Environmental Science. 2009; 6(14):142008.

L. Palen, S.B. Liu, Citizen communications in crisis: anticipating a future of ICT- supported public participation, in: CHI 2007 Proceedings • Emergency Action, 2007. Retrieved from http://www.hcitang.org/uploads/Teaching/palenliu- chi07.pdf.

L.I. Iezzoni, E.P. McCarthy, R.B. Davis, H. Siebens, Mobility difficulties are not only a problem of old age, J. Gen. Intern. Med. 16 (4) (2001) 235–243, https:// doi.org/10.1046/j.1525-1497.2001.016004235.x.*International Journal of Disaster Risk Reduction 54 (2021) 102043*

L.M. Holson, Nextdoor Is Betting a Social Network Can Still Be a Platform for Politics, The New York Times; Technology, 2018 https://www.nytimes.com/ 2018/07/13/technology/nextdoor-elections-politics-nyt.html.

Lin S., Lu Y., Justino J., Dong G., Lauper U. What Happened to Our Environment and Mental Health as a Result of Hurricane Sandy? Disaster Medicine and Public Health Preparedness. 2016; 10 (3):314–9. https://doi.org/10.1017/dmp.2016.51 PMID: 27087495

Lindell M.K., Hwang S.N. Households' Perceived Personal Risk and Responses in a Multihazard Environment. Risk Analysis. 2008; 28: 539–556. https://doi.org/10.1111/j.1539-6924.2008.01032.x

Lindell, M. K., & Perry, R. W. (2012). The protective action decision model: Theoretical modifications and additional evidence. *Risk Analysis*, *32*(4), 616–632. https://doi. org/10.1111/j.1539-6924.2011.01647.x.

Linkov I., Bridges T., Creutzig F., Decker J., Fox-Lent C., Kroger W., et al. Changing the resilience paradigm. National Climate Change. 2014; 4(6):407–409.

Linkov I., Palma-Oliveira J.M. An Introduction to Resilience for Critical Infrastructures. In: Linkov I., Palma-Oliveira J. (eds) Resilience and Risk. NATO Science for Peace and Security Series C: Environ- mental Security. Springer, Dordrecht. (2017).

M. Cameron, R. Power, B. Robinson, J. Yin, Emergency Situation Awareness from Twitter for Crisis Management, 2012. WWW 2012 – SWDM'12 Workshop. Retrieved from https://www2012.universite-lyon.fr/proceedings/companion/ p695.pdf.

M. Favaretto, E. De Clercq, B.S. Elger, Big Data and discrimination: perils, promises and solutions. A systematic review, J Big Data 6 (2019) 12, https://doi. org/10.1186/s40537-019-0177-4.

M. Gardoni, M. Spadoni, F. Vernadat, Harnessing non-structured information and knowledge and know-how capitalisation in integrated engineering: case study at aerospatiale matra, Concurr. Eng. 8 (4) (2000) 281–296, https://doi.org/ 10.1177/1063293x0000800403.

M. Haight, A. Quan-Haase, B.A. Corbett, Revisiting the digital divide in Canada: the impact of demographic factors on access to the internet, level of online activity, and social networking site usage, Information, Communication & Society 17 (4) (2014) 503–519, https://doi.org/10.1080/1369118X.2014.891633.

M. Micheli, Social networking sites and low-income teenagers: between opportunity and inequality, Inf. Commun. Soc. 19 (5) (2016) 565–581, https:// doi.org/10.1080/1369118X.2016.1139614.

M.E. Keim, E. Noji, Emergent use of social media: a new age of opportunity for disaster resilience, Am J Disaster Med 6 (1) (2011 Jan-Feb) 47–54. PMID: 21466029.

M.F. Goodchild, J.A. Glennon, Crowdsourcing geographic information for disaster response: a research frontier, Int. J. Digital Earth 3 (3) (2010) 231–241, https://doi.org/10.1080/17538941003759255. M.F. Goodchild, L. Li, Assuring the quality of volunteered geographic information, Spat. Statis. 1 (2012) 110–120, https://doi.org/10.1016/j.spasta.2012.03.00.

M.K. Lindell, S.N. Hwang, Households' perceived personal risk and responses in a multihazard environment, Risk Anal. 28 (2008) 539–556, https://doi.org/ 10.1111/j.1539-6924.2008.01032.x.

M.M. Malik, H. Lamba, C. Nakos, J. Pfeffer, Population bias in geotagged tweets, in: Ninth International AAAI Conference on Web and Social Media, 2015, April.

Marsh, B., Parnell, A. M., and Joyner, A. M. (2010). "Institutionalization of Racial Inequality in Local Political Geographies." *Urban Geography*, 31(October 2014), 691–709.

Martuzzi M., Mitis F., Forastiere F. Inequalities, inequities, environmental justice in waste management and health. European Journal of Public Health. 2010; 20:21–26. https://doi.org/10.1093/eurpub/ ckp216

McDonald J.H. Handbook of Biological Statistics (3rd ed.). Sparky House Publishing, Baltimore, Maryland. 2014; 209–212.

Mendoza, M., Poblete, B., Castillo, C. Twitter under Crisis: Can We Trust what We RT? 1st Workshop on Social Media Analytics (SOMA '10), 2010. Retrieved from http://snap.stanford.edu/soma2010/papers/soma2010_11.pdf.

Miles S.B. Foundations of community disaster resilience: well-being, identity, services, and capitals. Environmental Hazards. 2015; 14(2):103–21.

Mohai P., Saha R. Which came first, people or pollution? Assessing the disparate siting and post-siting demographic change hypotheses of environmental injustice. Environmental Research Letters. 2015; 10(11):115008.

Morrow Hearn, Peacock Gillis, Gladwin. Hurricane Andrew: ethnicity, gender, and the sociology of disasters, Routledge, London; New York. 1997.

Mostafavi A., Ganapati N.E. Toward Convergence Disaster Research: Building Integrative Theories Using Simulation. Risk Analysis.

Myers D.G., Diener E. Who Is Happy? Psychological Science. 1995; 6(1):10–9.

Horley J., Lavery J.J. Subjective well-being and age. Social Indicators Research. 1995; 34(2):275–82. https://doi.org/10.1007/BF01079200

Nadine Sarter, David Woods, Situation awareness: a critical but ill-defined phenomenon, Int. J. Aviat. Psychol. 1 (1991), https://doi.org/10.1207/ s15327108ijap0101_4.

Naik, N. K., Kominers, S. D., Raskar, R., Glaeser, E. L., & Hidalgo, C. A. (2015). *Do people shape cities, or do cities shape people? The Co- evolution of physical, social, and economic change in five major U.S. Cities.* Harvard Kennedy School Faculty Research Working Paper Series, RWP15-061. Retrieved fromhttps://pdfs.semanticscholar.org/cd0d/ fd293c6e3b8db9ec2c294212ef108c79c2f5.pdf.

Najafi, J., Peiravi, P., & Guerrero, J. P. (2018). Power distribution system improvement planning under hurricanes based on a new resilience index. *Sustainable Cities and Society, 39*, 592–604. https://doi.org/10.1016/j.scs.2018.03.022.

Najafi, M., Ardalan, A., Akbarisari, A., Noorbala, A. A., & Elmi, H. (2017). The theory of planned behavior and disaster preparedness. *PLoS Currents, 9*. https://doi.org/10. 1371/currents.dis.4da18e0f1479bf6c0a94b29e0dbf4a72 ecurrents.dis. 4da18e10f1479bf1476c1470a1494b1429e1470dbf1474a1472.

Nateghi R., Guikema S.D., Quiring S.M. Comparison and Validation of Statistical Methods for Predicting Power Outage Durations in the Event of Hurricanes. Risk Analysis. 2011; 31(12):1897–906. https://doi.org/10.1111/j.1539-6924.2011.01618.x PMID: 2148892

National Research Council. (2013). Subjective Well-Being: Measuring Happiness, Suffering, and Other Dimensions of Experience. Panel on Measuring Subjective Well-Being in a Policy-Relevant Framework. Stone A.A. and Mackie C., Editors. Committee on National Statistics, Division of Behavioral and Social Sciences and Education. Washington, DC: The National Academies Press.

National Research Council. Disaster Resilience: A National Imperative. Washington, DC: The National Academies Press. 2012. https://doi.org/10.17226/13457

National Weather Service (NWS), Hurricane Florence: September 14, 2018. National Oceanic and Atmospheric Administration (NOAA), 2018 (Retrieved from: https://www.weather.gov/ilm/HurricaneFlorence).

National Weather Service (NWS), Hurricane Michael: October 10, 2018. National Oceanic and Atmospheric Administration (NOAA), 2018. Retrieved from:https:// www.weather.gov/tae/HurricaneMichael2018.

Nextdoor, How to Use Nextdoor in a Natural Disaster or Illness Outbreak, 2020 (Retrieved from:https://help.nextdoor.com/s/article/How-to-use-Nextdoor-in-a- natural-disaster?language=en_US).

NIST (2016). *Community resilience planning guide for buildings and infrastructure systems.* Retrieved from Gaithersburg, MD.

NIST. Community Resilience Planning Guide for Buildings and Infrastructure Systems. Gaithersburg, MD.: National Institute of Standards and Technology; 2016.

Norris F.H., Friedman M.J., Watson P.J., Byrne C.M., Diaz E., Kaniasty K. 2002. 60,000 disaster victims speak: part I. An empirical review of the empirical literature, 1981–2001. Psychiatry: Interpersonal Biology Processes. 65(3):207–239. https://doi.org/10.1521/psyc.65.3.207.20173

Nozhati, S., Sarkale, Y., Ellingwood, B.R., Chong, E.K.P., Mahmoud, H. A Modified Approximate Dynamic Programming Algorithm for Community-level Food Security Following Disasters. 9th International Congress on Environmental Modelling and Software Fort Collins, Colorado, USA, 2018.

NRC. Disaster Resilience: A National Imperative. Washington, DC: The National Academies Press; 2012. 260 p.

Nyamwanza A.M. Livelihood resilience and adaptive capacity: A critical conceptual review. Jàmba´ : Journal of Disaster Risk Studies. 2012; 4(1).

OECD. OECD Guidelines on Measuring Subjective Well-being. Paris: OECD 2013. UNDRR. Sendai Framework for Disaster Risk Reduction. UN Office for Disaster Risk Reduction. Available online: https://www.unisdr.org/we/coordinate/sendai-framework (accessed on 9 June 2019).

Organization WH. Mental Health: New Understanding, New Hope. The World Health Report 2001.

Ottoni, R., Pesce, J. P., Casas, D. L., Jr, G., Meira Jr, W., Kumaraguru, P., & Almeida, V. (2013). Ladies first: Analyzing gender roles and behaviors in Pinterest. *Proceedings of the 7th International Conference on Weblogs and Social Media, ICWSM 2013*, 457-465.

Pampel F.C., Krueger P.M., Denney J.T. Socioeconomic Disparities in Health Behaviors. Annual Review Sociology 2010; 36:349–70.25.

Peters, C., Broersma, MJ. (Eds.), Rethinking Journalism: Trust and Participation in a Transformed News Landscape, 1st ed., Routledge, 2012 https://doi.org/ 10.4324/9780203102688

R. Cohen, D. Ruths, Classifying Political Orientation on Twitter: It's Not Easy! International AAAI Conference on Weblogs and Social Media, 2013.

R. Garett, E. Krueger, S. Young, Racial disparities in social media use, sexual risk behaviors, and HIV/AIDS stigma among men who have sex with men. HIV & AIDS Review, Int. J. HIV-Related Prob. 17 (3) (2018) 176–180, https://doi.org/ 10.5114/hivar.2018.78489.

R. Gaspar, S. Gorjao, B. Seibt, L. Lima, J. Barnett, A. Moss, Tweeting during food crises: a psychosocial analysis of threat coping expressions in Spain, during the 2011 European EHEC outbreak, Int J Hum Comput Stud 72 (2014) 239–254.

R. Li, A. Suh, Factors Influencing Information credibility on Social Media Platforms: Evidence from Facebook Pages, Procedia Computer Science 72 (2015) 314–328, https://doi.org/10.1016/j.procs.2015.12.146.

R. Liu, A. Suh, Factors influencing information credibility on social media platforms: evidence from Facebook pages. The thirds information systems international conference, Procedia Computer Sci. 72 (2015) 314–328, https:// doi.org/10.1016/j.procs.2015.12.146.

R. Muttarak, W. Lutz, Is education a key to reducing vulnerability to natural disasters and hence unavoidable climate change? Ecol. Soc. 19 (1) (2014) https:// doi.org/10.5751/ES-06476-190142.

R. Samuels, J.E. Taylor, Applied methodology for identifying hurricane-induced social media signal changes in vulnerable populations, in: ASCE Computing in Civil Engineering 2019, 2019.

R.E. Wilson, S.D. Gosling, L.T. Graham, A review of Facebook research in the social sciences, Perspect. Psychol. Sci. 7 (3) (2012) 203–220, https://doi.org/ 10.1177/1745691612442904.

R.L. Briones, B. Kuch, B.F. Liu, Y. Jin, Keeping up with the digital age: how the American Red Cross uses social media to build relationships, Public Relations. Rev. 37 (1) (2011) 37–43, https://doi.org/10.1016/j.pubrev.2010.12.006.

R.L. Pfefferbaum, R. Klomp, Community resilience, disasters, and the public's health, in: F.G. Murphy (Ed.), Community Engagement, Organization and Development for Public Health Practice, Springer, New York, 2013, pp. 275–298.

Raman, S. (2010). Designing a liveable compact city: Physical forms of city and social life in urban neighbourhoods. *Built Environment (1978)*, *36*(1), 63–80. Retrieved from http://www.jstor.org/stable/23289984.

Rand K., Kurth M., Fleming C. H., & Linkov I. A resilience matrix approach for measuring and mitigating disaster-induced population displacement. International Journal of Disaster Risk Reduction. 2020; 42: e10131

Rasoulkhani K., Mostafavi A. Resilience as an emergent property of human-infrastructure dynamics: A multi-agent simulation model for characterizing regime shifts and tipping point behaviors in infrastructure systems. PLOS ONE. 2018; 13(11). https://doi.org/10.1371/journal.pone.0207674 PMID: 30462719

Rasoulkhani, K., & Mostafavi, A. (2018). Resilience as an emergent property of human-infrastructure dynamics: A multi-agent simulation model for characterizing regime shifts and tipping point behaviors in infrastructure systems. *PloS One, 13*(11), Article e0207674. https://doi.org/10.1371/journal.pone.0207674.

Rasoulkhani, K., Mostafavi, A., Sharvelle, S., & Cole, J. (2019). Resilience-based infra-structure planning and asset management: Study of dual and singular water distribution infrastructure performance using a simulation approach. *Sustainable Cities and Society, 48*. https://doi.org/10.1016/j.scs.2019.101577.

Reeskens T., Vandecasteele L. Economic Hardship and Well-Being: Examining the Relative Role of Individual Resources and Welfare State Effort in Resilience Against Economic Hardship. Journal of Happiness Studies. 2017; 18(1):41–62.

Resseger, M. (2013). *The impact of land use regulation on racial segregation: Evidence from Massachusetts zoning borders. Harvard University Working Paper*.

Risser, M. D., & Wehner, M. F. (2017). Attributable human-induced changes in the likelihood and magnitude of the observed extreme precipitation during Hurricane Harvey. *Geophysical Research Letters, 44*, 7. https://doi.org/10.1002/2017GL075888.

Rogers, R. W. (1983). *Cognitive and physiological processes in fear appeals and attitude change: A revised theory of protection motivation.* New York, New York: Guildford Press.

Román M.O., Stokes E.C., Shrestha R., Wang Z., Schultz L., Carlo E.A.S., et al. Satellite-based assessment of electricity restoration efforts in Puerto Rico after Hurricane Maria. PLOS ONE. 2019; 14 (6): e0218883. https://doi.org/10.1371/journal.pone.0218883 PMID: 31251791

Rose D.J., Bodor N., Rice J.C., Swalm C.M., Hutchinson P.L. The Effects of Hurricane Katrina on Food Access Disparities in New Orleans American Journal of Public Health 101. 2011; 482:484. https://doi.org/10.2105/AJPH.2010.196659

RTI International. "Vulnerable populations disproportionately affected by food security, despite public programs." ScienceDaily, 25 July 2014. www.sciencedaily.com/releases/2014/07/140725080156.htm

Rufat, S., Tate, E., Burton, C. G., & Maroof, A. S. (2015). Social vulnerability to floods: Review of case studies and implications for measurement. *International Journal of Disaster Risk Reduction, 14*, 470–486. https://doi.org/10.1016/j.ijdrr.2015.09.013.

Ryan, B. (2013) “Information seeking in a flood”, Disaster Prevention and Management, Vol 22, No. 3, pp 229- 242.

S. Nagar, A. Seth, A. Joshi, Characterization of Social Media Response to Natural Disasters, 2012. WWW 2012 – SWDM’12 Workshop.

S. Nicholls, The resilient community and communication practice, Aust. J. Energy. Management. 27 (2012) 46–51.

S. Vieweg, A.L. Hughes, K. Starbird, L. Palen, Microblogging during Two Natural Hazards Events: what Twitter May Contribute to Situational Awareness, 2010. CHI 2010. Retrieved from https://cmci.colorado.edu/~palen/vieweg_1700_ chi2010.pdf.

S. Vosoughi, D. Roy, S. Aral, The spread of true and false news online, Science 359 (6380) (2018) 1146, https://doi.org/10.1126/science.aap9559.

S.E. Chang, T. McDaniels, J. Fox, R. Dhariwal, H. Longstaff, Toward Disaster- Resilient Cities: Characterizing Resilience of Infrastructure Systems with Expert Judgments, Risk Analysis 34 (3) (2014) 416–434, https://doi.org/10.1111/ risa.12133

S.L. Cutter, K.D. Ash, C.T. Emrich, Urban-rural differences in disaster resilience, Ann. Assoc. Am. Geogr. 106 (6) (2016) 1236–1252, https://doi.org/10.1080/ 24694452.2016.119474.

S.P. Borgatti, C. Rob, A relational view of information seeking and learning in social networks, Management. Sci. 49 (4) (2003) 432–445. Retrieved from www.jstor. org/stable/4133949.

Sangha K.K., Le Brocque A., Costanza R., Cadet-James Y. Application of capability approach to assess the role of ecosystem services in the well-being of Indigenous Australians. Global Ecology and Conservation. 2015; 4:445–58.50.

Santos JR, Herrera LC, Yu KDS, Pagsuyoin SAT, Tan RR. State of the Art in Risk Analysis of Work- force Criticality Influencing Disaster Preparedness for Interdependent Systems. Risk Analysis. 2014; 34(6):1056–68. https://doi.org/10.1111/risa.12183

Schimmack U., Oishi S. (2005). The influence of chronically and temporarily accessible information on life satisfaction judgments. Journal of Personality and Social Psychology, 89(3), 395–406. https://doi. org/10.1037/0022-3514.89.3.395 PMID: 16248721

Seetharaman, D, Wells, G. Hurricane Harvey victims turn to social media for assistance, The Wall Street J. (2017) https://www.wsj.com/articles/hurricane- harvey-victims-turn-to-social-media-for-assistance-1503999001.

Sen A. Commodities and Capabilities. Amsterdam: North-Holland; 1985.

Serulle-Urena, C. Accessibility of Low-Income Populations to Safe Zones during Localized Evacuations. Transportation Research Record. 2014; 2459:1,72–80. https://doi.org/10.3141/2459-09

Shear M.K., McLaughlin K.A., Ghesquiere A., Gruber M.J., Sampson N.A., Kessler R.C. Complicated grief associated with Hurricane Katrina. Depress. Anxiety. 2011; 28(8):648–657. https://doi.org/10. 1002/da.20865

Shumate, M. (2014). Social Networks and Popular Understanding of Science and Health: Sharing Disparities, by Southwell, Brian. *Health communication, 30*, 1-2. doi:10.1080/10410236.2014.885375.

Siamak S., Sattar T.M., Johnson K, Clavin C., Segura C., McCabe S., et al. Research Needs to Sup- port Immediate Occupancy Building Performance Objective Following Natural Hazard Events. NIST Special Publication 1224. 2018(1224):95. https://doi.org/10.6028/NIST.SP.1224

Silverman W.K., La Greca A.M. Children experiencing disasters: Definitions, reactions, and predictors of outcomes. In La Greca A. M., Silverman W. K., Vernberg E. M., & Roberts M. C. (Eds.), Helping children cope with disasters and terrorism (pp. 11–33). 2002. Washington, DC, US: American Psychological Association. https://doi.org/10.1037/10454-001

Smith, A., Anderson, M. (2018). Social media use in 2018 (Report). Retrieved from http://www.pewinternet.org/2018/03/01/social-media-use-in-2018/ Google Scholar.

Song J., Huang B., Li R. Assessing local resilience to typhoon disasters: A case study in Nansha, Guangzhou. PLOS ONE. 2018; 13(3): e0190701. https://doi.org/10.1371/journal.pone.0190701 PMID: 29522526

Stewart-Brown S., Samaraweera P.C., Taggart F., Kandala N.B., Stranges S. Socioeconomic gradients and mental health: implications for public health. British Journal of Psychiatry. 2015; 206(6):461– 5. https://doi.org/10.1192/bjp.bp.114.147280 PMID: 25792696

Stiglitz, J.E., Sen, A., Fitoussi, J.P. Report by the commission on the measurement of economic performance and social progress. Inoperability Input-Output Model for Interdependent Infrastructure Sec- tors. I: Theory and Methodology. 2010.

Stough L, Kang D. The Sendai Framework for Disaster Risk Reduction and Persons with Disabilities. International Journal of Disaster Risk Science. 2015; 6. https://doi.org/10.1007/s13753-015-0051-8. 39

Stringer, L., Quinn, C., Berman, R., Le, H., Msuya, F., Orchard, S., ... Pezzuti, J. (2014). *Combining nexus and resilience thinking in a novel framework to enable more equitable and just outcomes. Sustainability research institute, centre for climate change economics and policy working paper No. 193*.

Suleman Y., Agyemang-Duah W. Solid Waste Disposal and Community Health Implications in Ghana: Evidence from Sawaba, Asokore Mampong Municipal Assembly. Journal of Civil and Environmental Engineering. 2015; 5. https://doi.org/10.4172/2165-784X.1000202

Syed, S. T., Gerber, B. S., & Sharp, L. K. (2013). Traveling towards disease: transportation barriers to health care access. *Journal of Community Health*, *38*(5), 976–993. https://doi.org/10.1007/s10900-013-9681-1.

T. Correa, Digital skills and social media use: how Internet skills are related to different types of Facebook use among ‘digital natives, Information, Communication & Society 19 (8) (2016) 1095–1107, https://doi.org/10.1080/ 1369118X.2015.1084023.

T. Ludwig, C. Reuter, T. Siebigteroth, V. Pipek, CrowdMonitor: mobile crowd sensing for assessing physical and digital activities of citizens during emergencies, in: Paper Presented at the Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, Seoul, Republic of Korea, 2015.

Takahashi B, Tandoc EC Jr, Carmichael C (2015) Communicating on twitter during a disaster: an analysis of tweets during typhoon Haiyan in the Philippines. Comput Hum Behav 50:392–398.

Terrapon-Pfaff, J., Ortiz, W., Dienst, C., & Gröne, M.-C. (2018). Energising the WEF nexus to enhance sustainable development at local level. *Journal of Environmental Management, 223*, 409–416. https://doi.org/10.1016/j.jenvman.2018.06.037.

Thomas, K., Hardy, R. D., Lazrus, H., Mendez, M., Orlove, B., Rivera-Collazo, I., Roberts, J. T., Rockman, M., Warner, B. P., & Winthrop, R. (2019). Explaining differential vulnerability to climate change: A social science review. *Wiley interdisciplinary reviews Climate change, 10*(2), https://doi.org/10.1002/wcc.565 e565.

Tufekci, Z. Big Questions for Social Media Big Data: Representativeness, Validity and Other Methodological Pitfalls, 2014. *International Journal of Disaster Risk Reduction 54 (2021) 102043.*

U. S. Department of Health and Human Services. With understanding and improving health and objectives for improving health. 2nd ed. 2 vols. Washington: U. S. Government Printing Office; 2000. Healthy People 2010

Uchida Y., Takahashi Y., Kawahara K. Changes in Hedonic and Eudaimonic Well-Being After a Severe Nationwide Disaster: The Case of the Great East Japan Earthquake. Journal of Happiness Studies. 2014; 14(3). https://doi.org/10.1007/s10902-013-9463-6.

UNISDR (2013). Disaster Risk Reduction in the United Nations: Roles, Mandates, and results of key UN entities. Retrieved from: https://www.unisdr.org/files/32918_ drrintheun2013.pdf .

Ursano R.J., Fullerton C.S., Weisaeth L., Raphael B. Textbook of Disaster Psychiatry. Cambridge: Cambridge University Press; 2007. https://doi.org/10.1080/20008198.2018.1468711

US Census Bureau, 2018. (Retrieved from: https://www.census.gov/quickfacts/ TX).

US Census Bureau, 2018. Retrieved from: https://www.census.gov/quickfacts/TX van Deursen, van Dijk, The digital divide shifts to differences in usage, New Media & Society 16 (3) (2013) 507–526, https://doi.org/10.1177/1461444813487959.

VanDerslice, J. (2011). Drinking water infrastructure and environmental disparities: Evidence and methodological considerations. *American Journal of Public Health, 101 Suppl 1*(Suppl 1), S109–S114. https://doi.org/10.2105/AJPH.2011.300189.

Vaportzis E., Clausen M.G., Gow A.J. Older Adults Perceptions of Technology and Barriers to Interacting with Tablet Computers: A Focus Group Study. Front Psychol. 2017; 4;8:1687. https://doi.org/10. 3389/fpsyg.2017.01687 PMID: 29071004

Vaughan, E., Tinker, T. Effective health risk communication about pandemic influenza for vulnerable populations, Am. J. Publ. Health 99 (S2) (2009) S324–S332, https://doi.org/10.2105/ajph.2009.162537.

Ver Ploeg, M., Nulph, D., & Williams, R. B. (2011). *Mapping food deserts in the U.S. Amber waves:The economics of food, farming, natural resources, and Rural America.* 120966. Retrieved fromhttps://EconPapers.repec.org/RePEc:ags:uersaw:120966.

Viswanath, K., Kreuter, MW. Health disparities, communication inequalities, and eHealth, Am. J. Prev. Med. 32 (5 Suppl) (2007) S131–S133, https://doi.org/ 10.1016/j.amepre.2007.02.012.

W.Y.S. Chou, Y.M. Hunt, E.B. Beckjord, R.P. Moser, B.W. Hesse, Social media use in the United States: implications for health communication, J. Med. Internet Res.11 (4) (2009) e48, https://doi.org/10.2196/jmir.1249. S.R. Hiltz, A.L. Hughes, M. Imran, L. Plotnick, R. Power, M. Turoff, Exploring the usefulness and feasibility of software requirements for social media use in emergency management, Int. J. Disas. Risk Reduct. 42 (2020) 101367, https:// doi.org/10.1016/j.ijdrr.2019.101367.

Walker D.T. The 2017 Hurricane Season: A review of emergency response and energy infrastructure recovery efforts. Public Utility Commission of Texas. 2017.

Wamsler, C., & Brink, E. (2016). The urban domino effect: A conceptualization of cities' interconnectedness of risk. *International Journal of Disaster Resilience in the Built Environment, 7*(2), 33. https://doi.org/10.1108/IJDRBE-01-2015-0001.

WFAA. Mandatory evacuations ordered in some coastal Texas cities ahead of Harvey.2017: https:// www.wfaa.com/article/weather/mandatory-evacuations-ordered-in-some-coastal-texas-cities-ahead- of-harvey/287-466984235.

Wolbring Keuschnigg, N. (2011). Needs, Comparisons, and Adaptation: The Importance of Relative Income for Life Satisfaction. European Sociological Review. 29. https://doi.org/10.2307/ 23357107. 71

X. Guan, C. Chen, Using social media data to understand and assess disasters, Nat. Hazards 74 (2) (2014) 13, https://doi.org/10.1007/s11069-014-1217-1.

Y. Jiang, Z. Li, X. Ye, Understanding demographic and socioeconomic biases of geotagged twitter users at the county level, Cartography. Geography. Inf. Sci. 46 (3) (2019) 228–242.

Y. Xiao, Q. Huange, K. Wu, Understanding social media data for disaster management, Nat. Hazards 79 (2015) 16, https://doi.org/10.1007/s11069-015- 1918-0.

Yang, Y., Thomas Ng, S., Zhou, S., Xu, F. J., & Li, H. (2020). Physics-based resilience assessment of interdependent civil infrastructure systems with condition-varying components: A case with stormwater drainage system and road transport system. *Sustainable Cities and Society*, 54. https://doi.org/10.1016/j.scs.2019.101886.

Yu, M., Q. Huang, Q, Qin, H., Scheele, C., Yang, C. Deep learning for real-time social media text classification for situation awareness – using Hurricanes Sandy, Harvey, and Irma as case studies, Int. J. Digital Earth 12 (11) (2019) 1230–1247, https://doi.org/10.1080/17538947.2019.1574316.

Z. Wang, N.S.N. Lam, N. Obradovich, X. Ye, Are vulnerable communities digitally left behind in social responses to natural disasters? An evidence from Hurricane Sandy with Twitter data, Appl. Geography. 108 (2019) 1–8, https://doi.org/10.1016/ j.apgeog.2019.05.001.

Zemba V., Wells E. M., Wood M. D., Trump B. D., Boyle B., Blue S., et al. Defining, measuring, and enhancing resilience for small groups. Safety Science. 2019; 120: 603–616. https://doi.org/10.1016/j. ssci.2019.07.042

Zhu, j., Manandhar, J., Truong, J., Ganapati, E., Pradhananga, N., Davidson, R., Mostafavi, A. (2017). Assessment of infrastructure resilience in the 2015 gorkha earthquake. *Earthquake Spectra, 33*(S1), 18.

APPENDIX A.

STUDY 2 SUPPLEMENTARY TABLES

Table 1A.. Percent of social media users from total households across hurricane events

Subgroup Population		Hurricane Event			
		Harvey # (%)	**Michael # (%)**	**Florence <# (%)**	**Total**
Race	White	640 (60)	488 (69)	397 (74)	1525
	Black-African American	208 (19)	164 (23)	97 (18)	469
	Asian	39 (4)	10 (1)	3 (1)	52
	Latino-Hispanic	128 (12)	12 (2)	28 (5)	168
	Other	60 (6)	32 (5)	48 (9)	140
		1075 (100)	706 (100)	573 (100)	2354
Income	< $25,000	160 (15)	178 (25)	112 (21)	450
	$25,000 - $49,999	232 (22)	188 (27)	140 (26)	560
	$50,000 - $74,999	240 (22)	138 (20)	138 (26)	516
	$75,000 - $99,999	144 (13)	92 (13)	65 (12)	301
	$100,000- $124,999	94 (9)	46 (7)	47 (9)	187
	$125,000- $149,999	78 (7)	27 (4)	33 (6)	138
	> $150,000	127 (12)	37 (5)	38 (7)	202
Education	Bachelor's Degree or Higher	851 (79)	512 (73)	471 (88)	1834
	High School or Equivalent	195 (18)	175 (25)	97 (18)	467
	None	23 (2)	16 (2)	5 (1)	44
	Other	6 (1)	3 (0)	4 (1)	13
Health	Chronic	329 (31)	271 (38)	184 (34)	784
	Disability	134 (12)	94 (13)	88 (16)	316
Social Media Used	Yes	721 (67)	439 (62)	397 (74)	1557
Social Media Platform	Facebook	406 (38)	267 (38)	234 (44)	907
	Twitter	126 (12)	15 (2)	42 (8)	183
	Nextdoor	146 (14)	13 (2)	64 (12)	223
	Other	75 (7)	15 (2)	22 (4)	112
Geographic Location (Urban-Rural)		1076 (100)	442 (62)	397 (69)	1915

Table 2A. Difference in Social Media Platform according to Geographic Factors

Group	Platform	DF	Sum Sq	Mean Sq	F-Value	P
Storm Event	Nextdoor	2	4.21	2.1057	15.81	1.59e-07
		R:1542	***R:***204.71	***R:***0.133		
	Twitter	2	1.07	0.5370	4.28	0.014
		R:1554	***R:***194.95	***R:***0.1255		
	Facebook	2	0.53	0.26407	2.719	0.0662
		R:1544	***R:***149.23	***R:*** 0.097		
Urban-Rural	Nextdoor	1	4.84	4.835	36.44	1.96e-09
		R:1543	***R:***204.71	***R:*** 0.133		
	Twitter	1	1.51	1.5081	12.02	0.001
		R:1554	***R:***194.95	***R:***0.1255		
	Facebook	1	1.55	1.552	16.16	6.1e-05
		R:1543	***R:***148.18	***R:*** 0.096		

**R = residual error.

Table 3A. Income, Education, and Health(Mobility) ANOVA-1 Results

	Social Media Platform Group	Df	Sum Sq	Mean Sq	F value	Pr (>F)
HEALTH: Mobility	Nextdoor	2	0.01	0.01437	0.106	0.745
		R:1551	***R:***200.0	***R:***0.1290		
	Twitter	2	3.23	0.8076	6.501	3.46e-05
		R:1554	***R:***192.79	***R:***0.124		
	Facebook	2	2.16	0.4320	4.489	0.001
		R: 1543	***R:*** 149.32	***R:*** 0.0968		
EDUCATION	Nextdoor	2	2.76	1.381	10.30	0.000
		R:1542	***R:***206.78	***R:***0.134		
	Twitter	2	0.604	0.302	2.397	0.0913
		R:1542	***R:***194.40	***R:***0.1261		
	Facebook	2	0.040	0.022	0.231	0.794
		R:1542	***R:***149.69	***R:***0.097		
INCOME	Nextdoor	5	10.5	2.099	16.28	1.12e-15
		R:1551	***R:***200.0	***R:***0.129		
	Twitter	5	0.640	0.127	1.001	0.411

	Social Media Platform Group	Df	Sum Sq	Mean Sq	F value	Pr (>F)
		R:1539	***R:***194.42	***R:***0.126		
	Facebook	5	2.16	0.4320	4.527	0.000
		R:1539	***R:***147.56	***R:***0.096		

**R = residual error.

Table 4A. Disparities in Information Reliability on Social Media, ANOVA-1 Way Test

	Reliability Group	Df	Sum Sq	Mean Sq	F value	Pr (>F)
RACE& ETHNICITY	*Not at all*	4	0.072	0.018	1.407	0.229
		1540	19.669	0.013		
	Somewhat unreliable	4	0.690	0.172	2.43	0.046
		R: 1540	***R:***109.15	***R:***0.071		
	Neutral	4	2.84	0.711	5.099	0.000
		154	214.73	0.139		
	Somewhat reliable	4	12.5	3.121	13.150	1.56e-10
		R:1540	***R:***365.6	***R:***0.237		
	Very Reliable	4	2.86	0.716	3.525	0.007
		R:1540	***R:***312.69	***R:***0.203		
EDUCATION	*Not at all*	2	0.193	0.097	7.629	0.001
		R:1542	***R:***19.548	***R:***0.013		
	Somewhat unreliable	2	0.11	0.053	0.746	0.475
		R:154	***R:***109.73	***R:***0.071		
	Neutral	2	1.11	0.554	3.948	0.020
		R:1542	***R:***216.46	***R:***0.140		
	Somewhat reliable	5	5.30	1.060	4.375	0.001
		R:1539	***R:***372.8	***R:***0.242		
	Very Reliable	2	2.11	1.054	5.184	0.006
		R:1542	***R:***313.44	***R:***0.20		
INCOME	*Not at all*	5	0.089	0.018	1.396	0.223
		1539	19.652	0.013		
	Somewhat unreliable	5	0.36	0.071	1.004	0.414

	Reliability Group	Df	Sum Sq	Mean Sq	F value	Pr (>F)
		R:153	***R:***109.48	***R:***0.071		
	Neutral	5	0.6	0.121	0.858	0.509
		R:1539	***R:***217.0	***R:***0.141		
	Somewhat reliable	5	5.3	1.060	4.375	0.001
		R:1539	***R:***372.8	***R:***0.242		
	Very Reliable	5	0.39	0.080	0.382	0.861
		R:1539	***R:***315.16	***R:***0.205		

*****R*** = residual error.

Table 5A. Information seeking activity during storms by racial and ethnic group; Hurricane Harvey

	Info Checked	Estimate	Std. Error	Wald	Sig.	OR
Asian	Intercept	−3.400	0.740	−4.590	<0.001	0.033
	Flooding Status	−1.160	1.150	−1.010	0.313	0.314
	Weather	0.165	0.469	0.353	0.724	1.180
	Supermarket	−1.130	0.494	−2.280	0.023	0.324
	Road Condition	0.526	0.611	0.860	0.390	1.692
	Damages	0.894	0.470	1.900	0.057	2.444
	Service Status	1.040	1.300	0.799	0.424	2.833
Black and African American	Intercept	0.717	0.661	1.080	0.278	2.048
	Flooding Status	0.126	0.220	0.572	0.567	1.134
	Weather	0.145	0.213	0.680	0.496	1.156
	Supermarket	−0.378	0.260	−1.450	0.147	0.685
	Road Condition	0.285	0.210	1.360	0.175	1.330
	Damages	−0.745	0.726	−1.030	0.305	0.475
	Service Status	−1.610	0.402	−4.020	0.000	0.199
Latino and Hispanic	Intercept	1.490	1.060	1.400	0.160	4.419
	Flooding Status	0.169	0.274	0.618	0.536	1.184
	Weather	0.420	0.262	1.600	0.110	1.522
	Supermarket	−0.356	0.327	−1.090	0.277	0.700
	Road Condition	0.134	0.258	0.519	0.604	1.143
	Damages	−1.510	1.130	−1.340	0.181	0.221
	Service Status	−3.920	1.040	−3.770	<0.001	0.020

	Info Checked	Estimate	Std. Error	Wald	Sig.	OR
Other	Intercept	0.612	1.090	0.563	0.574	1.844
	Flooding Status	0.052	0.394	0.131	0.896	1.053
	Weather	0.474	0.365	1.300	0.194	1.606
	Supermarket	−0.538	0.463	−1.160	0.245	0.584
	Road Condition	0.684	0.401	1.700	0.089	1.981
	Damages	0.756	1.490	0.506	0.613	2.131
	Service Status	−3.400	0.740	−4.590	<0.001	0.033

*OR = Odds Ratio.

Table 6A. Information seeking activity during storms by racial and ethnic group; Hurricane Michael

	Info Checked	Estimate	Std. Error	Wald	Sig.	OR
Asian	Intercept	−16.000	0.652	−24.500	<0.001	<0.001
	Flooding Status	0.884	1.52	0.580	0.562	2.420
	Weather	0.884	1.520	0.580	0.562	2.420
	Supermarket	−1.690	1.360	−1.250	0.213	0.185
	Road Condition	0.181	1.400	0.126	0.900	1.200
	Damages	13.400	0.652	0.200	<0.001	
	Service Status	−1.170	1.610	−0.726	0.468	0.311
Black and African American	Intercept	−0.482	1.300	−0.369	0.712	0.610
	Flooding Status	−1.170	1.610	−0.726	0.468	0.311
	Weather	−0.434	0.357	−1.220	0.224	0.648
	Supermarket	1.040	0.278	3.750	<0.001	2.830
	Road Condition	−0.752	0.271	−2.770	0.006	0.471
	Damages	−0.327	0.266	−1.230	0.219	0.721
	Service Status	0.801	0.266	3.010	0.003	2.230
Latino and Hispanic	Intercept	−0.752	0.271	−2.770	0.006	0.471
	Flooding Status	−0.052	0.295	−0.174	0.862	0.950
	Weather	−0.707	0.365	−1.940	0.053	0.493
	Supermarket	−3.130	1.180	−2.660	0.008	0.044
	Road Condition	0.947	0.806	1.180	0.240	2.580
	Damages	−0.779	0.732	−1.060	0.287	0.459

	Info Checked	Estimate	Std. Error	Wald	Sig.	OR
	Service Status	1.270	0.838	1.510	0.130	3.560
Other	Intercept	1.320	1.090	1.210	0.226	3.760
	Flooding Status	−1.510	0.757	−1.990	0.047	0.222
	Weather	−1.120	1.090	−1.020	0.305	0.326
	Supermarket	−1.990	0.665	−3.000	0.003	0.136
	Road Condition	0.274	0.537	0.511	0.609	1.320
	Damages	0.060	0.504	0.119	0.905	1.060
	Service Status	−0.088	0.518	−0.170	0.865	0.916

*OR = Odds Ratio.

Table 7A. Information seeking activity during storms by racial and ethnic group; Hurricane Florence

	Info Checked	Estimate	Std. Error	Wald	Sig.	OR
Asian	Intercept	−2.390	1.260	−1.900	0.058	0.092
	Flooding Status	12.200	0.674	18.100	<0.001	
	Weather	0.117	1.460	0.080	0.936	1.120
	Supermarket	14.900	0.674	22.100	<0.001	3
	Road Condition	−0.675	2.010	−0.335	0.737	0.509
	Damages	−19.000	<0.001	−3.56	<0.001	<0.001
	Service Status	−26.900	0.674	−40.000	<0.001	<0.001
Black and African American	Intercept	−0.728	0.474	−1.540	0.124	0.483
	Flooding Status	0.424	0.456	0.931	0.352	1.530
	Weather	−0.005	0.321	−0.017	0.987	0.995
	Supermarket	0.920	0.322	2.850	0.004	2.510
	Road Condition	−0.950	0.407	−2.340	0.019	0.387
	Damages	−0.277	0.331	−0.835	0.404	0.758
	Service Status	−0.607	0.626	−0.970	0.332	0.545
Latino and Hispanic	Intercept	−2.290	0.818	−2.800	0.005	0.101
	Flooding Status	−0.600	0.583	−1.030	0.304	0.549
	Weather	0.218	0.499	0.437	0.662	1.240
	Supermarket	−0.003	0.482	−0.005	0.996	0.997
	Road Condition	0.248	0.659	0.377	0.706	1.280

	Info Checked	Estimate	Std. Error	Wald	Sig.	OR
	Damages	−0.720	0.489	−1.470	0.141	0.487
	Service Status	0.365	0.926	0.395	0.693	1.440
Other	Intercept	−1.680	0.613	−2.740	0.006	0.186
	Flooding Status	0.191	0.680	0.280	0.779	1.210
	Weather	1.210	0.530	2.270	0.023	3.340
	Supermarket	−0.446	0.466	−0.958	0.338	0.640
	Road Condition	−0.557	0.541	−1.030	0.303	0.573
	Damages	−0.251	0.461	−0.544	0.586	0.778
	Service Status	−0.973	0.792	−1.230	0.219	0.378

*OR = Odds Ratio.

APPENDIX B.

STUDY 3: SEM Statistical Summaries (Model 1-6)

Table 1B. Model 1

	Estimate	Std. Err.	z	p
	Factor Loadings			
Infra.disruption				
days.water	1.00+			
days.power	1.68	0.28	6.07	0
days.food	3.27	0.59	5.5	0
days.transport	3.04	0.6	5.08	0
Urban_attributes				
grocery.dist	1.00+			
proxim.flood.infra	0.1	0.03	3.12	0.002
proxim.industrial.plant	0.12	0.03	4.37	0
Infra.Fail.Risk	3.45	0.69	5.03	0
FEMA.Floodzone	0.07	0.03	2.64	0.008
Behavior				
underestimate.storm	1.00+			
lack.transport	0.11	0.02	6.05	0
underestimate.disruptions	0.49	0.05	10.24	0
supply.costs	0.33	0.04	8.49	0
storage.space	0.19	0.03	6.5	0

supply.shortage	0.67	0.06	10.81	0
FEW_Vulnerability				
road.hardship	1.00+			
power.hardship	0.75	0.08	9.08	0
water.hardship	0.7	0.07	9.76	0
food.hardship	1.22	0.09	12.93	0
Regression Slopes				
FEW_Vulnerability				
Infra.disruption	1.52	0.33	4.56	0
Behavior	0.67	0.2	3.32	0.001
Behavior				
Urban.attributes	0.29	0.07	4.28	0
Infra.disruption				
Urban.attributes	0.48	0.12	3.88	0
		Residual Variances		
days.water	1.56	0.29	5.39	0
days.power	2.63	0.54	4.87	0
days.food	12.9	1.35	9.56	0
days.transport	21.52	2.62	8.22	0
grocery.dist	11.85	4.12	2.88	0.004
proxim.flood.infra	0.25	0	115.06	0
proxim.industrial.plant	0.07	0.01	8.94	0
Infra.Fail.Risk	10.81	1.07	10.14	0
FEMA.Floodzone	0.16	0.01	18.64	0
underestimate.storm	0.1	0.01	7.51	0
lack.transport	0.02	0	3.57	0
underestimate.disruptions	0.07	0.01	7.78	0
supply.costs	0.07	0.01	8.12	0
storage.space	0.05	0.01	7.2	0
supply.shortage	0.1	0.01	9.76	0
road.hardship	0.69	0.11	6.5	0
power.hardship	0.92	0.08	10.98	0
water.hardship	0.72	0.09	8.42	0
food.hardship	0.35	0.13	2.67	0.008
num.grocery	0.32	0.06	5.73	0
		Residual Covariances		
days.water w/days.power	0.46	0.17	2.8	0.005
days.food w/days.transport	2.83	0.9	3.16	0.002
days.transport w/road.hardship	1.24	0.26	4.74	0
days.water w/water.hardship	0.34	0.08	4.57	0

days.power w/power.hardship	0.74	0.13	5.77	0
days.food w/food.hardship	0.93	0.2	4.58	0
power.hardship w/water.hardship	0.29	0.07	4.27	0
road.hardship w/food.hardship	-0.34	0.1	-3.46	0.001
days.water w/power.hardship	0.2	0.08	2.71	0.007
days.power w/water.hardship	0.32	0.12	2.72	0.007
days.food w/underestimate.storm	0.26	0.07	3.53	0
proxim.flood.infra w/FEMA.Floodzone	0.04	0.01	5.92	0
FEMA.Floodzone w/road.hardship	0.07	0.02	3.82	0
days.transport w/proxim.flood.infra	0.21	0.08	2.54	0.011
days.transport w/underestimate.storm	0.24	0.08	2.92	0.003
supply.shortage w/num.grocery	-0.01	0.01	-1.86	0.062
days.food w/supply.shortage	0.25	0.06	3.89	0
road.hardship w/water.hardship	-0.14	0.07	-2.06	0.039
proxim.flood.infra w/road.hardship	0.06	0.02	2.86	0.004
proxim.industrial.plant w/FEMA.Floodzone	0.01	0	2.55	0.011
Latent Variances				
Infra.disruption	0.07	0.03	2.39	0.017
Urban.attributes	0.3	0.11	2.66	0.008
Behavior	0.06	0.01	6.4	0
FEW.Vulnerability	0.19	0.08	2.28	0.023
		<u>Fit Indices</u>		
$\chi 2$	132.41(147)			0.8
CFI	1			
TLI	1.01			
RMSEA	0			

+Fixed parameter

Table 2B. Model 2	Estimate	Std. Err.	z	p
		<u>Factor Loadings</u>		
<u>Infra.disruption</u>				
days.water	1.00+			
days.power	1.71	0.28	6.06	0
days.food	3.1	0.57	5.41	0
days.transport	2.92	0.58	4.99	0
Behavior				
underestimate.storm	1.00+			

lack.transport	0.13	0.02	6.91	0
underestimate.disruptions	0.5	0.05	10.71	0
supply.costs	0.37	0.04	9.45	0
storage.space	0.19	0.03	6.63	0
supply.shortage	0.66	0.06	11.24	0
FEW_Vulnerability				
road.hardship	1.00+			
power.hardship	0.82	0.08	10.13	0
water.hardship	0.77	0.07	10.96	0
food.hardship	1.22	0.09	13.65	0
Urban_attributes				
Infra.Fail.Risk	1.00+			
FEMA.Floodzone	0.02	0.01	2.97	0.003
grocery.dist	0.29	0.06	5	0
proxim.flood.infra	0.03	0.01	3.6	0
proxim.industrial.plant	0.03	0.01	6.2	0
Regression Slopes				
Behavior				
Urban.attributes	0.08	0.02	3.62	0
Minority	0.09	0.02	4.1	0
Education	-0.02	0.01	-2	0.045
Income	-0.02	0.01	-2.37	0.018
Infra.disruption				
Urban.attributes	0.13	0.04	3.15	0.002
FEW_Vulnerability				
Urban.attributes	0.27	0.07	3.77	0
Minority	0.26	0.05	5.36	0
Education	-0.05	0.02	-3.16	0.002
Income	-0.03	0.01	-2.3	0.021
		Residual Variances		
days.water	1.54	0.29	5.28	0
days.power	2.54	0.55	4.65	0
days.food	12.81	1.37	9.36	0
days.transport	21.41	2.63	8.14	0
underestimate.storm	0.1	0.01	8.12	0
lack.transport	0.02	0	3.5	0
underestimate.disruptions	0.07	0.01	7.89	0
supply.costs	0.06	0.01	7.84	0
storage.space	0.05	0.01	7.23	0
supply.shortage	0.1	0.01	10.24	0

road.hardship	0.75	0.1	7.84	0
power.hardship	0.89	0.08	10.59	0
water.hardship	0.68	0.09	7.94	0
food.hardship	0.43	0.11	3.83	0
Infra.Fail.Risk	10.81	1.25	8.65	0
FEMA.Floodzone	0.16	0.01	18.62	0
grocery.dist	11.86	4.12	2.88	0.004
proxim.flood.infra	0.25	0	114.29	0
proxim.industrial.plant	0.07	0.01	8.89	0
num.grocery	0.32	0.06	5.73	0
Minority	0.24	0	68.01	0
Education	3.07	0.12	26.06	0
Income	3.63	0.13	27.29	0
		Residual Covariances		
days.water w/days.power	0.42	0.17	2.43	0.015
days.food w/days.transport	2.73	0.92	2.96	0.003
days.transport w/road.hardship	1.28	0.26	4.96	0
days.water w/water.hardship	0.33	0.08	4.36	0
days.power w/power.hardship	0.71	0.13	5.56	0
days.food w/food.hardship	1.01	0.2	5.08	0
power.hardship w/water.hardship	0.26	0.07	3.75	0
road.hardship w/food.hardship	-0.27	0.09	-3.1	0.002
days.water w/power.hardship	0.19	0.08	2.54	0.011
days.power w/water.hardship	0.3	0.12	2.48	0.013
days.food w/underestimate.storm	0.27	0.07	3.62	0
FEMA.Floodzone w/proxim.flood.infra	0.04	0.01	5.91	0
road.hardship w/FEMA.Floodzone	0.07	0.02	3.79	0
days.transport w/proxim.flood.infra	0.22	0.08	2.6	0.009
days.transport w/underestimate.storm	0.25	0.08	2.98	0.003
supply.shortage w/num.grocery	-0.01	0.01	-1.86	0.062
days.food w/supply.shortage	0.25	0.06	3.98	0
road.hardship w/water.hardship	-0.14	0.07	-2.19	0.028
road.hardship w/proxim.flood.infra	0.06	0.02	2.87	0.004
FEMA.Floodzone w/proxim.industrial.plant	0.01	0	2.52	0.012
Minority w/Education	-0.17	0.03	-5.85	0
Minority w/Income	-0.21	0.03	-6.97	0
Education w/Income	1.5	0.11	14.27	0
		Latent Variances		
Infra.disruption	0.1	0.05	2.16	0.031

Behavior	0.06	0.01	5.28	0
FEW.Vulnerability	0.28	0.09	3.07	0.002
Urban.attributes	3.52	0.94	3.76	0
Latent Covariances				
Infra.disruption w/Behavior	0	0.01	0.27	0.787
Infra.disruption w/FEW.Vulnerability	0.1	0.04	2.39	0.017
Behavior w/FEW.Vulnerability	0.02	0.02	1.12	0.262
Constructed				
indirect.effect	0.01	0.01	1.83	0.068
Total.effect	0.28	0.08	3.66	0
		<u>Fit Indices</u>		
χ2	267.75(199)			0.001
CFI	0.97			
TLI	0.97			
RMSEA	0.02			

+Fixed parameter

Table 3B. Model 3	Estimate	Std. Err.	z	p
		<u>Factor Loadings</u>		
<u>Infra.disruption</u>				
days.water	1.00+			
days.power	1.68	0.28	6.07	0
days.food	3.28	0.59	5.51	0
days.transport	3.07	0.6	5.09	0
<u>Urban_attributes</u>				
grocery.dist	1.00+			
proxim.flood.infra	0.1	0.03	3.12	0.002
proxim.industrial.plant	0.12	0.03	4.38	0
Infra.Fail.Risk	3.44	0.68	5.04	0
FEMA.Floodzone	0.07	0.03	2.64	0.008
<u>Behavior</u>				
underestimate.storm	1.00+			
lack.transport	0.11	0.02	6.15	0
underestimate.disruptions	0.49	0.05	10.36	0

supply.costs	0.34	0.04	8.76	0
storage.space	0.19	0.03	6.61	0
supply.shortage	0.68	0.06	11.04	0
FEW_Vulnerability				
road.hardship	1.00+			
power.hardship	0.73	0.08	9.22	0
water.hardship	0.68	0.07	9.95	0
food.hardship	1.2	0.09	13.18	0
		Regression Slopes		
FEW_Vulnerability				
Infra.disruption	1.59	0.35	4.54	0
Behavior	0.6	0.22	2.68	0.007
Kids	0.13	0.04	2.89	0.004
Behavior				
Urban.attributes	0.29	0.07	4.28	0
Kids	0.09	0.02	4.53	0
Infra.disruption				
Urban.attributes	0.48	0.12	3.88	0
		Residual Variances		
days.water	1.56	0.29	5.4	0
days.power	2.63	0.54	4.89	0
days.food	12.91	1.35	9.58	0
days.transport	21.52	2.62	8.22	0
grocery.dist	11.85	4.12	2.88	0.004
proxim.flood.infra	0.25	0	114.63	0
proxim.industrial.plant	0.07	0.01	8.94	0
Infra.Fail.Risk	10.81	1.07	10.13	0
FEMA.Floodzone	0.16	0.01	18.63	0
underestimate.storm	0.1	0.01	7.77	0
lack.transport	0.02	0	3.57	0
underestimate.disruptions	0.07	0.01	7.89	0
supply.costs	0.07	0.01	8.03	0
storage.space	0.05	0.01	7.2	0
supply.shortage	0.1	0.01	9.69	0
road.hardship	0.67	0.11	6.18	0
power.hardship	0.92	0.08	11.14	0
water.hardship	0.72	0.09	8.48	0
food.hardship	0.34	0.13	2.67	0.008
num.grocery	0.32	0.06	5.73	0
Kids	0.58	0.07	7.96	0

		Residual Covariances		
days.water w/days.power	0.47	0.16	2.83	0.005
days.food w/days.transport	2.84	0.9	3.16	0.002
days.transport w/road.hardship	1.22	0.26	4.66	0
days.water w/water.hardship	0.34	0.07	4.6	0
days.power w/power.hardship	0.74	0.13	5.83	0
days.food w/food.hardship	0.94	0.2	4.61	0
power.hardship w/water.hardship	0.3	0.07	4.35	0
road.hardship w/food.hardship	-0.35	0.1	-3.59	0
days.water w/power.hardship	0.21	0.07	2.75	0.006
days.power w/water.hardship	0.33	0.12	2.75	0.006
days.food w/underestimate.storm	0.26	0.07	3.55	0
proxim.flood.infra w/FEMA.Floodzone	0.04	0.01	5.92	0
FEMA.Floodzone w/road.hardship	0.07	0.02	3.79	0
days.transport w/proxim.flood.infra	0.21	0.08	2.53	0.011
days.transport w/underestimate.storm	0.24	0.08	2.93	0.003
supply.shortage w/num.grocery	-0.01	0.01	-1.86	0.062
days.food w/supply.shortage	0.25	0.06	3.87	0
road.hardship w/water.hardship	-0.14	0.07	-2.16	0.031
proxim.flood.infra w/road.hardship	0.06	0.02	2.83	0.005
proxim.industrial.plant w/FEMA.Floodzone	0.01	0	2.54	0.011
		Latent Variances		
Infra.disruption	0.06	0.03	2.38	0.017
Urban.attributes	0.3	0.11	2.67	0.008
Behavior	0.06	0.01	6.11	0
FEW.Vulnerability	0.19	0.09	2.16	0.031
		Fit Indices		
χ^2	165.15(165)			0.482
CFI	1			
TLI	1			
RMSEA	0			

$^{+}$Fixed parameter

Table 4B. Model 4

	Estimate	Std. Err.	z	p

		Factor Loadings		
Infra.disruption				
days.water	1.00+			
days.power	1.68	0.28	6.07	0
days.food	3.29	0.6	5.51	0
days.transport	3.08	0.6	5.09	0
Urban_attributes				
grocery.dist	1.00+			
proxim.flood.infra	0.1	0.03	3.11	0.002
proxim.industrial.plant	0.12	0.03	4.37	0
Infra.Fail.Risk	3.44	0.68	5.03	0
FEMA.Floodzone	0.07	0.03	2.64	0.008
Behavior				
underestimate.storm	1.00+			
lack.transport	0.11	0.02	6.18	0
underestimate.disruptions	0.49	0.05	10.27	0
supply.costs	0.33	0.04	8.6	0
storage.space	0.19	0.03	6.54	0
supply.shortage	0.67	0.06	10.9	0
FEW_Vulnerability				
road.hardship	1.00+			
power.hardship	0.73	0.08	9.15	0
water.hardship	0.67	0.07	9.77	0
food.hardship	1.22	0.09	13.11	0
		Regression Slopes		
FEW_Vulnerability				
Infra.disruption	1.56	0.34	4.56	0
Behavior	0.65	0.21	3.13	0.002
disability.health	0.17	0.07	2.53	0.011
Behavior				
Urban.attributes	0.29	0.07	4.28	0
disability.health	0.09	0.03	3.37	0.001
Infra.disruption				
Urban.attributes	0.48	0.12	3.88	0
Residual Variances				
days.water	1.56	0.29	5.4	0
days.power	2.63	0.54	4.88	0
days.food	12.89	1.35	9.55	0
days.transport	21.5	2.62	8.21	0
grocery.dist	11.85	4.12	2.88	0.004

proxim.flood.infra	0.25	0	114.73	0
proxim.industrial.plant	0.07	0.01	8.94	0
Infra.Fail.Risk	10.81	1.07	10.14	0
FEMA.Floodzone	0.16	0.01	18.63	0
underestimate.storm	0.1	0.01	7.64	0
lack.transport	0.02	0	3.56	0
underestimate.disruptions	0.07	0.01	7.85	0
supply.costs	0.07	0.01	8.08	0
storage.space	0.05	0.01	7.2	0
supply.shortage	0.1	0.01	9.73	0
road.hardship	0.67	0.11	6.23	0
power.hardship	0.92	0.08	11.07	0
water.hardship	0.73	0.08	8.67	0
food.hardship	0.33	0.13	2.52	0.012
num.grocery	0.32	0.06	5.73	0
disability.health	0.14	0.01	16.59	0
		Residual Covariances		
days.water w/days.power	0.46	0.17	2.82	0.005
days.food w/days.transport	2.82	0.9	3.14	0.002
days.transport w/road.hardship	1.22	0.26	4.68	0
days.water w/water.hardship	0.35	0.07	4.65	0
days.power w/power.hardship	0.74	0.13	5.81	0
days.food w/food.hardship	0.93	0.2	4.54	0
power.hardship w/water.hardship	0.3	0.07	4.42	0
road.hardship w/food.hardship	-0.36	0.1	-3.59	0
days.water w/power.hardship	0.21	0.07	2.74	0.006
days.power w/water.hardship	0.33	0.12	2.8	0.005
days.food w/underestimate.storm	0.26	0.07	3.54	0
proxim.flood.infra w/FEMA.Floodzone	0.04	0.01	5.92	0
FEMA.Floodzone w/road.hardship	0.07	0.02	3.8	0
days.transport w/proxim.flood.infra	0.21	0.08	2.53	0.011
days.transport w/underestimate.storm	0.24	0.08	2.92	0.003
supply.shortage w/num.grocery	-0.01	0.01	-1.86	0.062
days.food w/supply.shortage	0.25	0.06	3.88	0
road.hardship w/water.hardship	-0.13	0.07	-2.02	0.044
proxim.flood.infra w/road.hardship	0.06	0.02	2.84	0.004
proxim.industrial.plant w/FEMA.Floodzone	0.01	0	2.54	0.011
		Latent Variances		
Infra.disruption	0.06	0.03	2.4	0.016
Urban.attributes	0.3	0.11	2.66	0.008

Behavior	0.06	0.01	6.33	0
FEW.Vulnerability	0.2	0.09	2.27	0.023
		Fit Indices		
χ2	157.95(165)			0.639
CFI	1			
TLI	1			
RMSEA	0			

+Fixed parameter

Table 5B. Model 5

	Estimate	Std. Err.	z	p
		Factor Loadings		
Infra.disruption				
days.water	1.00+			
days.power	1.68	0.28	6.07	0
days.food	3.25	0.59	5.5	0
days.transport	3.02	0.59	5.08	0
Urban_attributes				
grocery.dist	1.00+			
proxim.flood.infra	0.1	0.03	3.12	0.002
proxim.industrial.plant	0.12	0.03	4.37	0
Infra.Fail.Risk	3.46	0.69	5.03	0
FEMA.Floodzone	0.07	0.03	2.64	0.008
Behavior				
underestimate.storm	1.00+			
lack.transport	0.11	0.02	5.97	0
underestimate.disruptions	0.49	0.05	10.33	0
supply.costs	0.32	0.04	8.55	0
storage.space	0.19	0.03	6.54	0
supply.shortage	0.67	0.06	10.96	0
FEW_Vulnerability				
road.hardship	1.00+			
power.hardship	0.76	0.08	9.23	0
water.hardship	0.72	0.07	9.98	0
food.hardship	1.23	0.09	13.02	0
Regression Slopes				
FEW_Vulnerability				
Infra.disruption	1.54	0.34	4.55	0

Behavior	0.6	0.21	2.91	0.004
prior.experience	-0.23	0.07	-3.19	0.001
Behavior				
Urban.attributes	0.29	0.07	4.28	0
prior.experience	-0.12	0.03	-4.09	0
Infra.disruption				
Urban.attributes	0.48	0.12	3.88	0
		Residual Variances		
days.water	1.56	0.29	5.39	0
days.power	2.63	0.54	4.87	0
days.food	12.92	1.35	9.58	0
days.transport	21.54	2.62	8.23	0
grocery.dist	11.85	4.12	2.88	0.004
proxim.flood.infra	0.25	0	115.32	0
proxim.industrial.plant	0.07	0.01	8.94	0
Infra.Fail.Risk	10.81	1.07	10.13	0
FEMA.Floodzone	0.16	0.01	18.64	0
underestimate.storm	0.1	0.01	7.42	0
lack.transport	0.02	0	3.59	0
underestimate.disruptions	0.07	0.01	7.82	0
supply.costs	0.07	0.01	8.15	0
storage.space	0.05	0.01	7.21	0
supply.shortage	0.1	0.01	9.7	0
road.hardship	0.71	0.1	6.81	0
power.hardship	0.92	0.08	10.97	0
water.hardship	0.71	0.09	8.25	0
food.hardship	0.36	0.13	2.83	0.005
num.grocery	0.32	0.06	5.73	0
prior.experience	0.13	0.01	15.24	0
		Residual Covariances		
days.water w/days.power	0.46	0.17	2.8	0.005
days.food w/days.transport	2.85	0.9	3.18	0.001
days.transport w/road.hardship	1.25	0.26	4.79	0
days.water w/water.hardship	0.34	0.08	4.5	0
days.power w/power.hardship	0.73	0.13	5.75	0
days.food w/food.hardship	0.94	0.2	4.62	0
power.hardship w/water.hardship	0.29	0.07	4.16	0
road.hardship w/food.hardship	-0.32	0.1	-3.39	0.001
days.water w/power.hardship	0.2	0.08	2.68	0.007
days.power w/water.hardship	0.32	0.12	2.65	0.008

days.food w/underestimate.storm	0.26	0.07	3.52	0
proxim.flood.infra w/FEMA.Floodzone	0.04	0.01	5.92	0
FEMA.Floodzone w/road.hardship	0.07	0.02	3.83	0
days.transport w/proxim.flood.infra	0.21	0.08	2.54	0.011
days.transport w/underestimate.storm	0.24	0.08	2.92	0.004
supply.shortage w/num.grocery	-0.01	0.01	-1.86	0.062
days.food w/supply.shortage	0.25	0.06	3.87	0
road.hardship w/water.hardship	-0.14	0.07	-2.11	0.035
proxim.flood.infra w/road.hardship	0.06	0.02	2.88	0.004
proxim.industrial.plant w/FEMA.Floodzone	0.01	0	2.55	0.011
		Latent Variances		
Infra.disruption	0.06	0.03	2.37	0.018
Urban.attributes	0.29	0.11	2.66	0.008
Behavior	0.06	0.01	6.3	0
FEW.Vulnerability	0.17	0.08	2.12	0.034
		Fit Indices		
$\chi 2$	172.31(165)			0.332
CFI	1			
TLI	1			
RMSEA	0.01			

$^{+}$Fixed parameter

Table 6B. Model 6

	Estimate	Std. Err.	z	p
		Factor Loadings		
Infra.disruption				
days.water	1.00^{+}			
days.power	1.68	0.28	6.06	0
days.food	3.12	0.56	5.53	0
days.transport	2.94	0.58	5.09	0
Urban_attributes				
grocery.dist	1.00^{+}			
proxim.flood.infra	0.1	0.03	3.14	0.002
proxim.industrial.plant	0.12	0.03	4.4	0
Infra.Fail.Risk	3.46	0.68	5.06	0
FEMA.Floodzone	0.07	0.03	2.64	0.008
Behavior				
underestimate.storm	1.00^{+}			

lack.transport	0.13	0.02	7.04	0
underestimate.disruptions	0.49	0.04	10.93	0
supply.costs	0.38	0.04	9.89	0
storage.space	0.19	0.03	6.81	0
supply.shortage	0.67	0.06	11.7	0
<u>FEW_Vulnerability</u>				
road.hardship	1.00^{+}			
power.hardship	0.79	0.08	10.46	0
water.hardship	0.75	0.07	11.31	0
food.hardship	1.2	0.09	14.15	0
		<u>Regression Slopes</u>		
<u>FEW_Vulnerability</u>				
Infra.disruption	1.62	0.36	4.55	0
Behavior	0.4	0.24	1.67	0.095
disability.health	0.13	0.07	1.97	0.049
prior.experience	-0.16	0.07	-2.11	0.035
Minority	0.19	0.06	3.32	0.001
Education	-0.04	0.02	-2.18	0.029
Income	-0.02	0.02	-1.55	0.12
Kids	0.08	0.04	1.88	0.06
<u>Behavior</u>				
Urban.attributes	0.28	0.06	4.31	0
disability.health	0.07	0.03	2.51	0.012
prior.experience	-0.08	0.03	-2.33	0.02
Minority	0.06	0.02	2.46	0.014
Education	-0.01	0.01	-1.22	0.224
Income	-0.01	0.01	-2.03	0.042
Kids	0.06	0.02	3.35	0.001
<u>Infra.disruption</u>				
Urban.attributes	0.48	0.12	3.9	0
		<u>Residual Variances</u>		
days.water	1.56	0.29	5.39	0
days.power	2.63	0.54	4.87	0
days.food	13.02	1.34	9.71	0
days.transport	21.6	2.62	8.26	0
grocery.dist	11.85	4.12	2.88	0.004
proxim.flood.infra	0.25	0	114.27	0
proxim.industrial.plant	0.07	0.01	8.92	0
Infra.Fail.Risk	10.74	1.08	9.98	0
FEMA.Floodzone	0.16	0.01	18.64	0

underestimate.storm	0.1	0.01	8.41	0
lack.transport	0.02	0	3.52	0
underestimate.disruptions	0.07	0.01	8.08	0
supply.costs	0.06	0.01	7.74	0
storage.space	0.05	0.01	7.23	0
supply.shortage	0.1	0.01	10.11	0
road.hardship	0.73	0.1	7.56	0
power.hardship	0.89	0.08	10.82	0
water.hardship	0.69	0.08	8.12	0
food.hardship	0.42	0.11	3.74	0
num.grocery	0.32	0.06	5.73	0
disability.health	0.14	0.01	16.58	0
prior.experience	0.13	0.01	15.24	0
Minority	0.24	0	68.01	0
Education	3.07	0.12	26.06	0
Income	3.63	0.13	27.29	0
Kids	0.58	0.07	7.95	0
		Residual Covariances		
days.water w/days.power	0.46	0.17	2.8	0.005
days.food w/days.transport	2.93	0.89	3.29	0.001
days.transport w/road.hardship	1.25	0.26	4.83	0
days.water w/water.hardship	0.33	0.08	4.36	0
days.power w/power.hardship	0.72	0.13	5.61	0
days.food w/food.hardship	0.98	0.2	4.95	0
power.hardship w/water.hardship	0.27	0.07	3.91	0
road.hardship w/food.hardship	-0.29	0.09	-3.31	0.001
days.water w/power.hardship	0.19	0.08	2.53	0.011
days.power w/water.hardship	0.3	0.12	2.52	0.012
days.food w/underestimate.storm	0.27	0.07	3.69	0
proxim.flood.infra w/FEMA.Floodzone	0.04	0.01	5.92	0
FEMA.Floodzone w/road.hardship	0.07	0.02	3.85	0
days.transport w/proxim.flood.infra	0.21	0.08	2.54	0.011
days.transport w/underestimate.storm	0.25	0.08	3.03	0.002
supply.shortage w/num.grocery	-0.01	0.01	-1.86	0.062
days.food w/supply.shortage	0.25	0.06	3.99	0
road.hardship w/water.hardship	-0.15	0.06	-2.26	0.024
proxim.flood.infra w/road.hardship	0.06	0.02	2.89	0.004
proxim.industrial.plant w/FEMA.Floodzone	0.01	0	2.54	0.011
disability.health w/prior.experience	0.01	0	2.43	0.015
disability.health w/Minority	0	0.01	0.07	0.947

disability.health w/Education	-0.1	0.02	-4.03	0
disability.health w/Income	-0.12	0.02	-4.96	0
disability.health w/Kids	0.02	0.01	1.5	0.132
prior.experience w/Minority	-0.03	0.01	-5.27	0
prior.experience w/Education	0.09	0.02	3.88	0
prior.experience w/Income	0.07	0.02	2.89	0.004
prior.experience w/Kids	-0.04	0.01	-3.56	0
Minority w/Education	-0.17	0.03	-5.85	0
Minority w/Income	-0.21	0.03	-6.97	0
Minority w/Kids	0.09	0.01	6.21	0
Education w/Income	1.5	0.11	14.27	0
Education w/Kids	-0.17	0.05	-3.55	0
Income w/Kids	-0.12	0.05	-2.32	0.021
		Latent Variances		
Infra.disruption	0.06	0.03	2.39	0.017
Urban.attributes	0.3	0.11	2.68	0.007
Behavior	0.05	0.01	5.96	0
FEW.Vulnerability	0.12	0.08	1.44	0.149
		Fit Indices		
χ^2	367.20(255)			0
CFI	0.96			
TLI	0.95			
RMSEA	0.02			

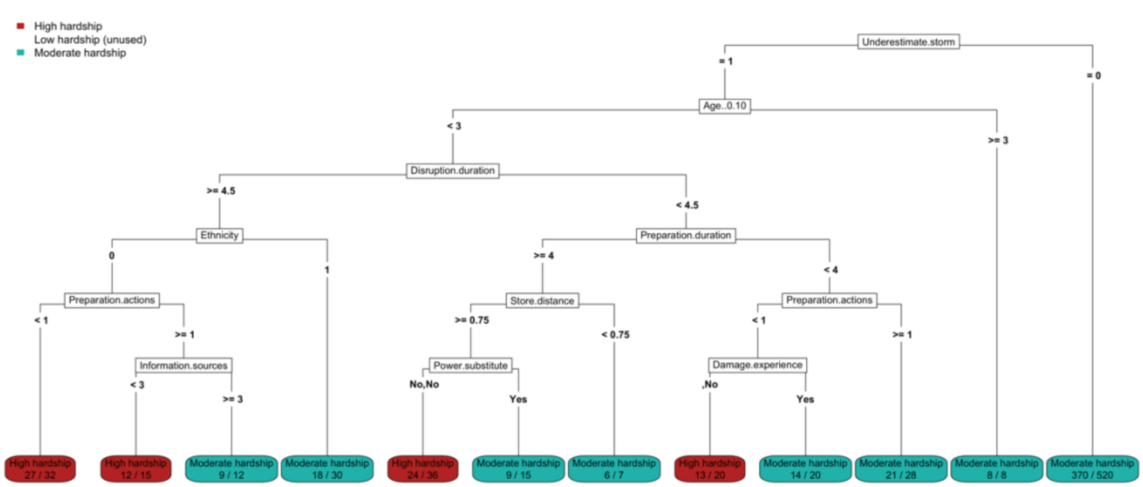
$^{+}$Fixed parameter

APPENDIX C.

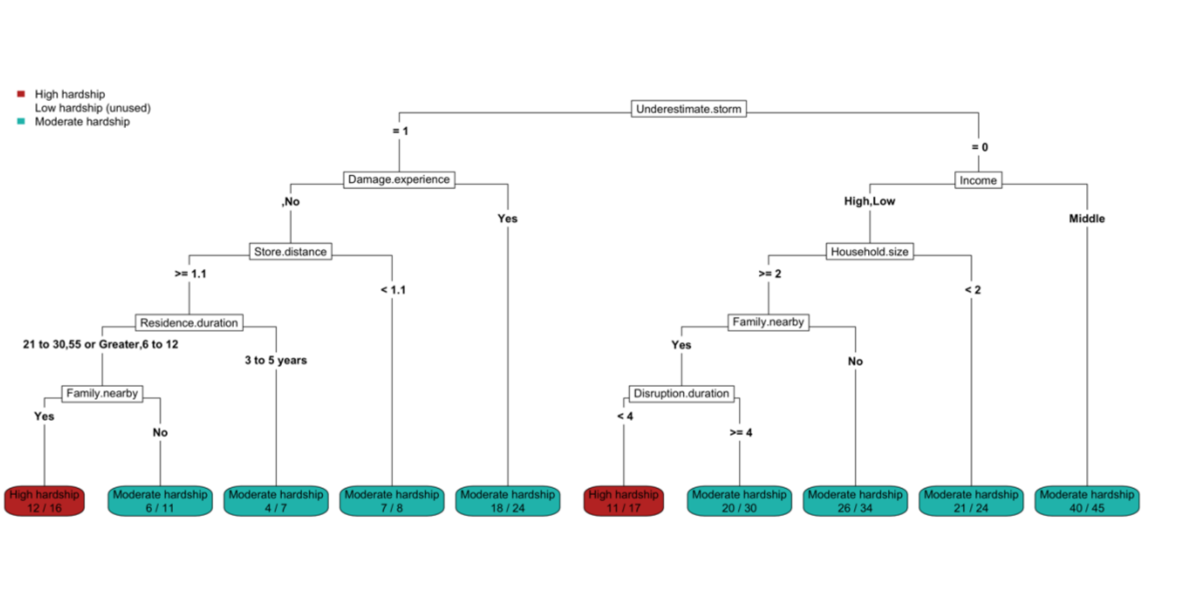
The full decision trees resulting from the analysis of the 24 CART models are provided in this section. This section is organized by Infrastructure System and the subsequent models (Income group, Ethnicity group, and "All") are provided.

Electricity Infrastructure

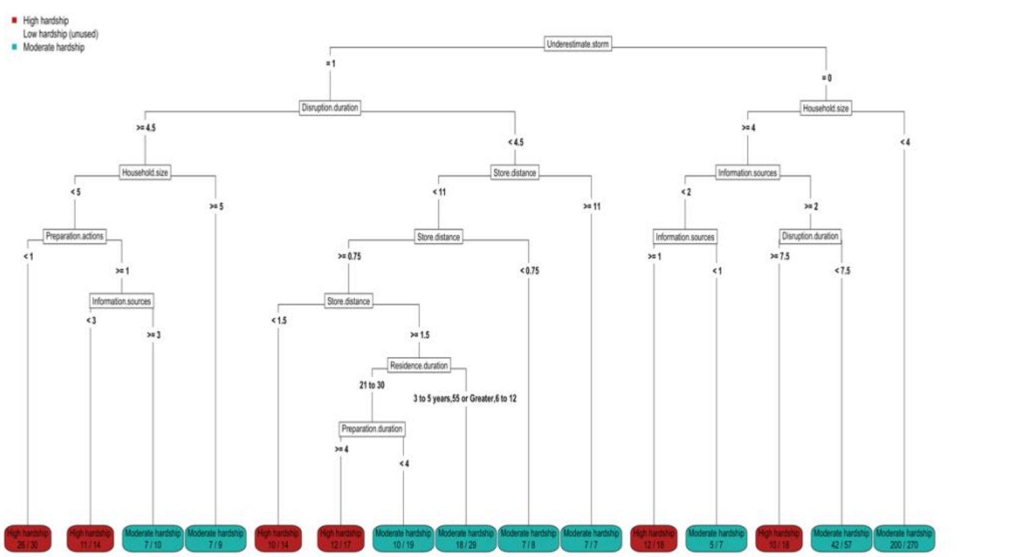
i. All groups



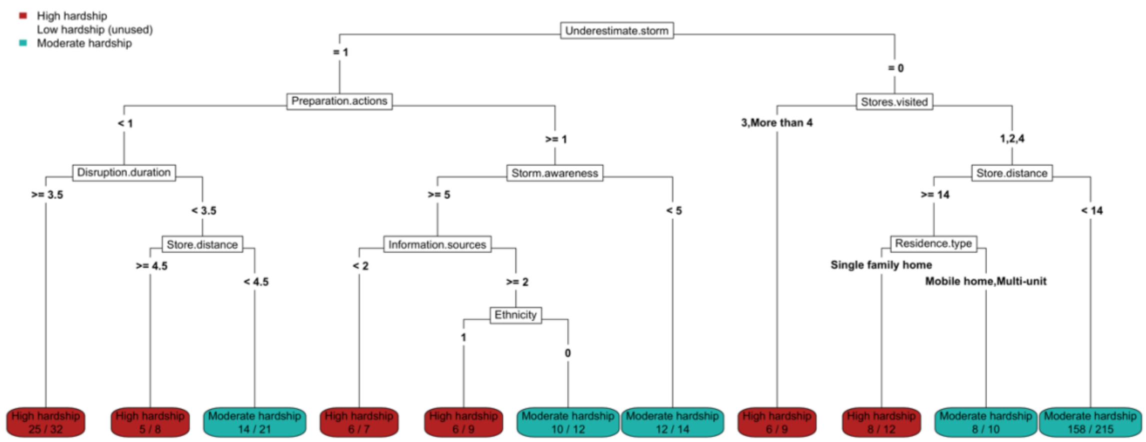
ii. Minority



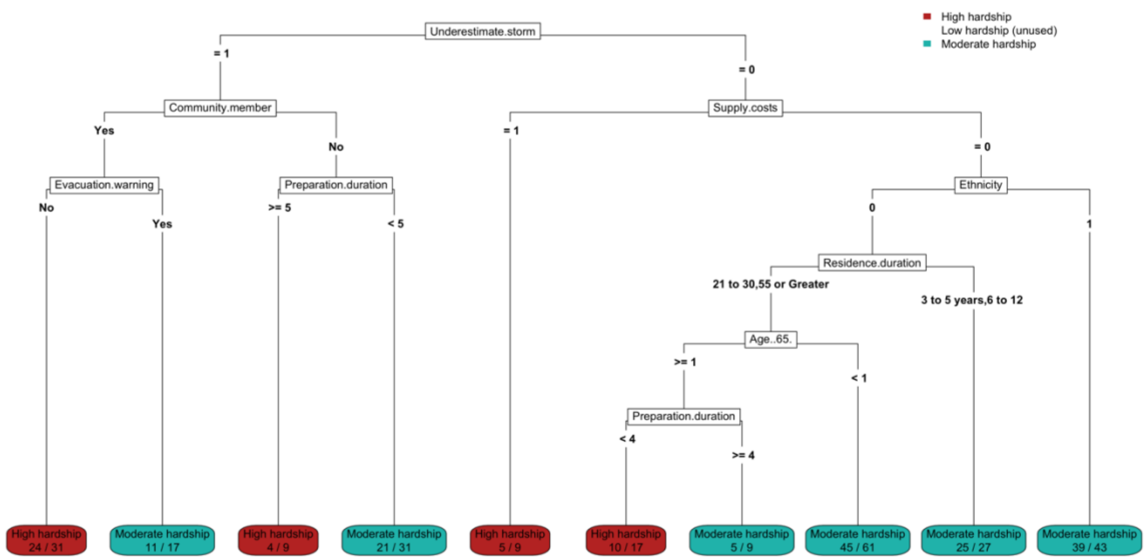
iii. White



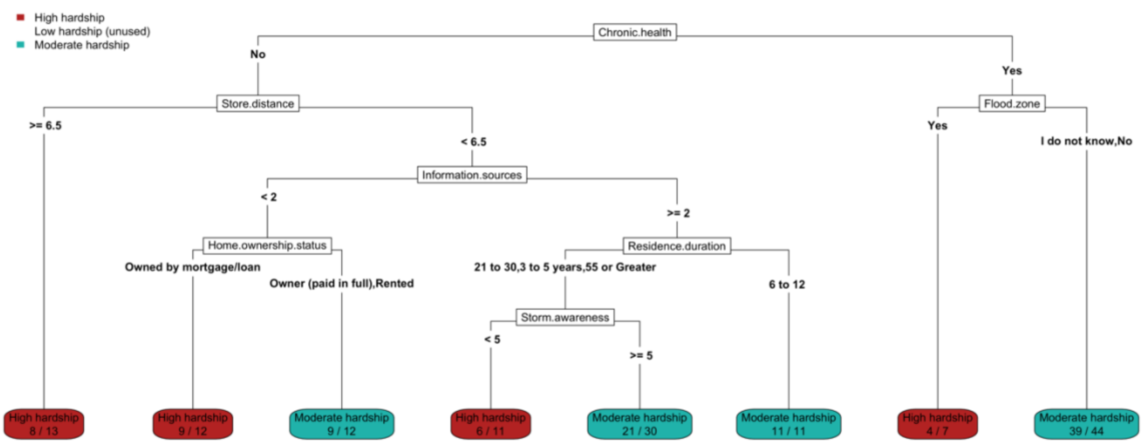
iv. Low Income



v. Middle Income

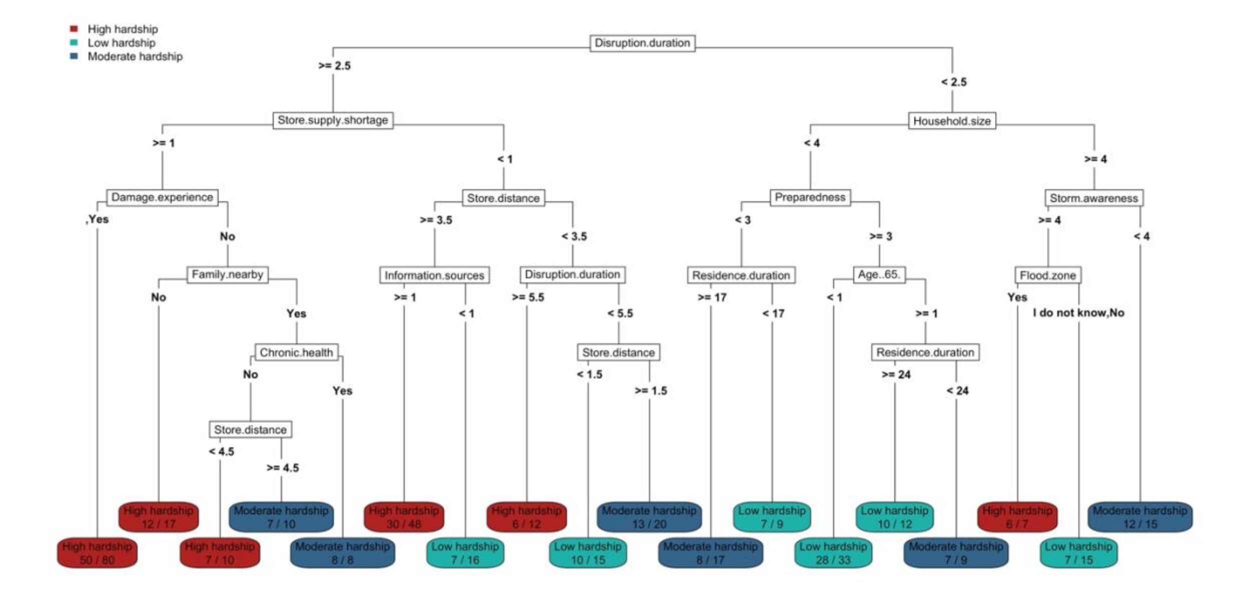


vi. High Income

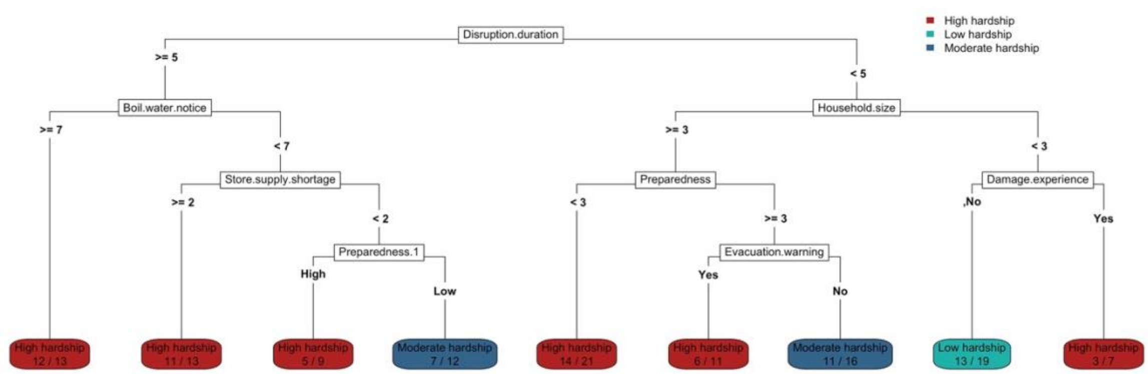


Water Infrastructure

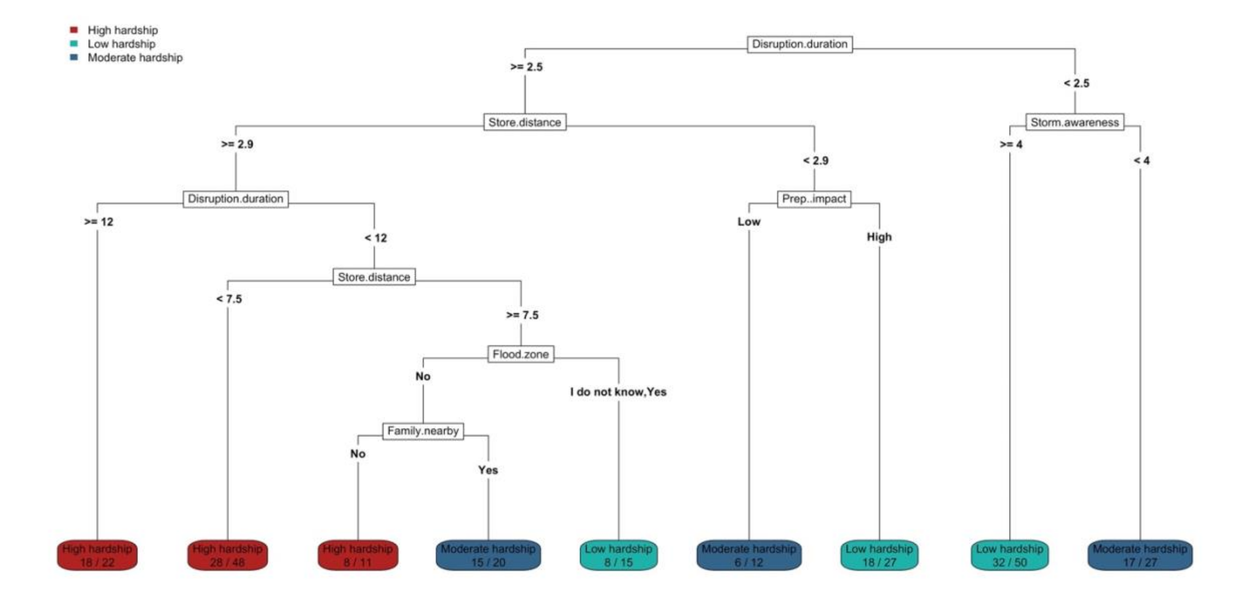
vii. All groups



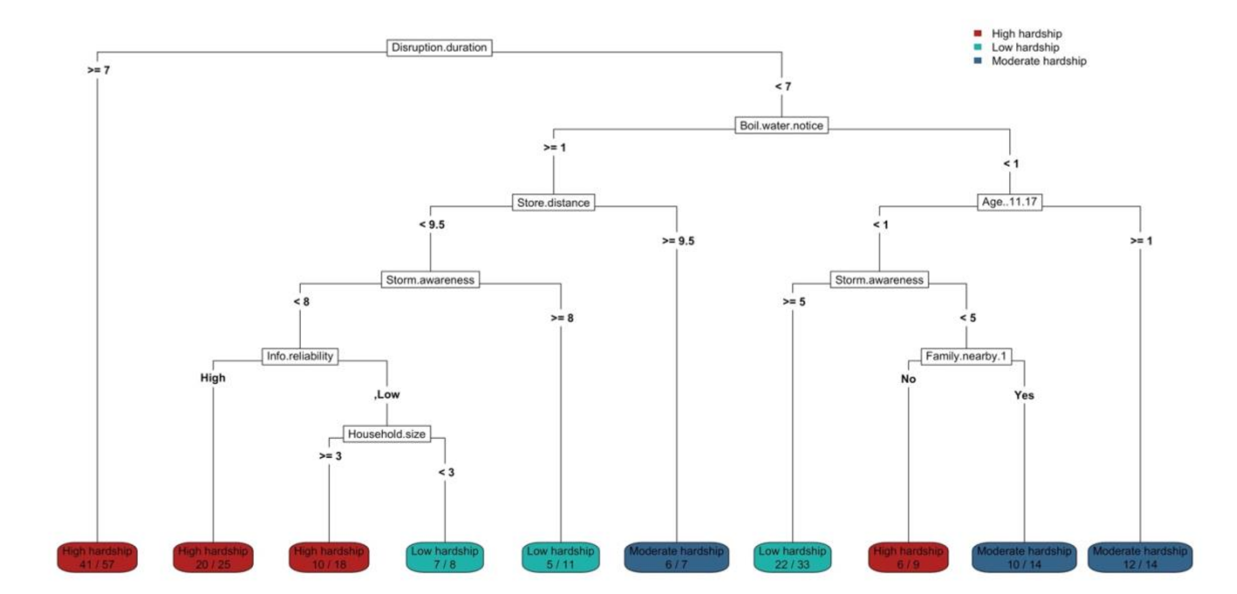
viii. Minority



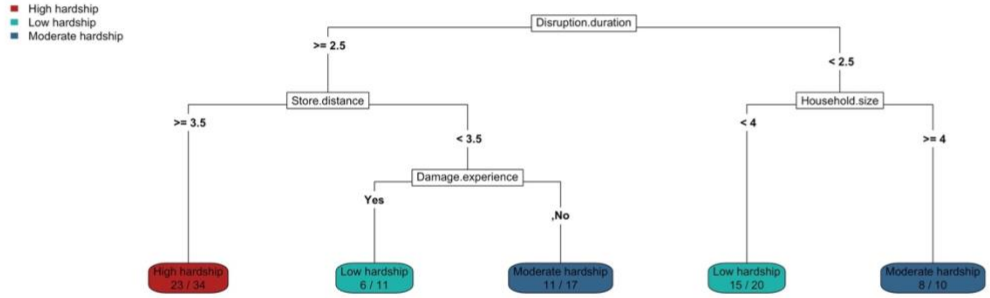
ix. White



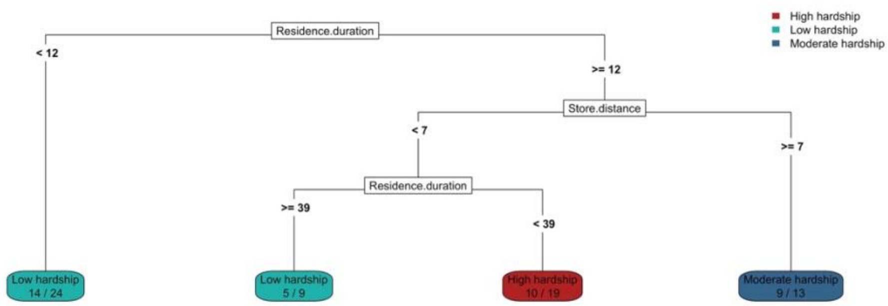
x. Low Income



xi. Middle Income

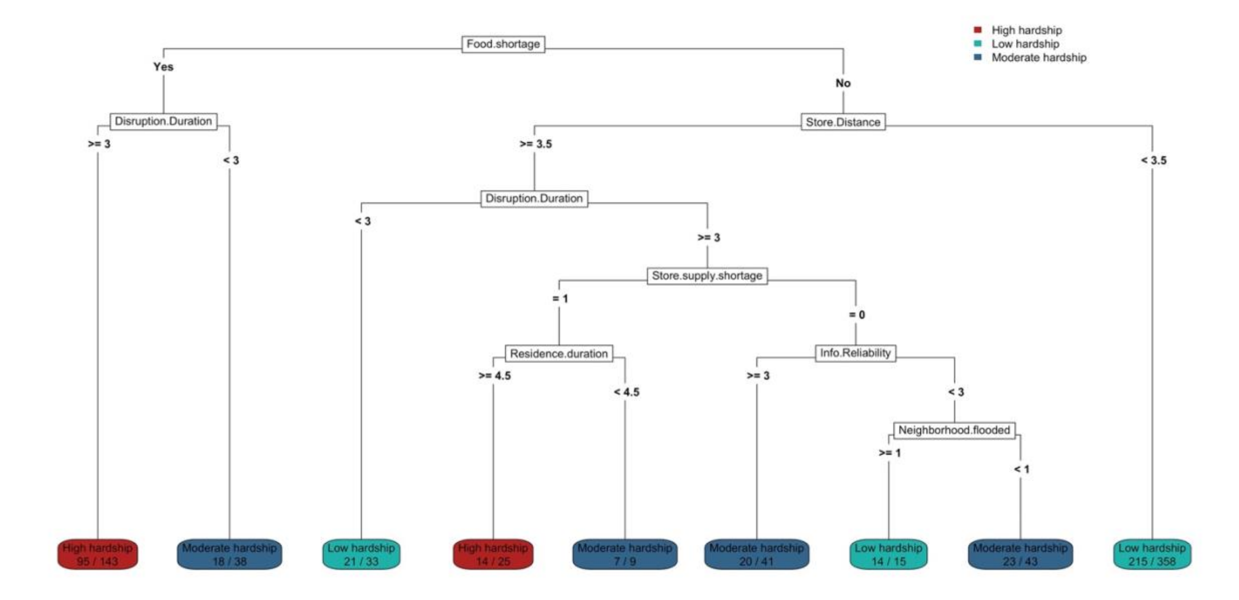


xii. High Income

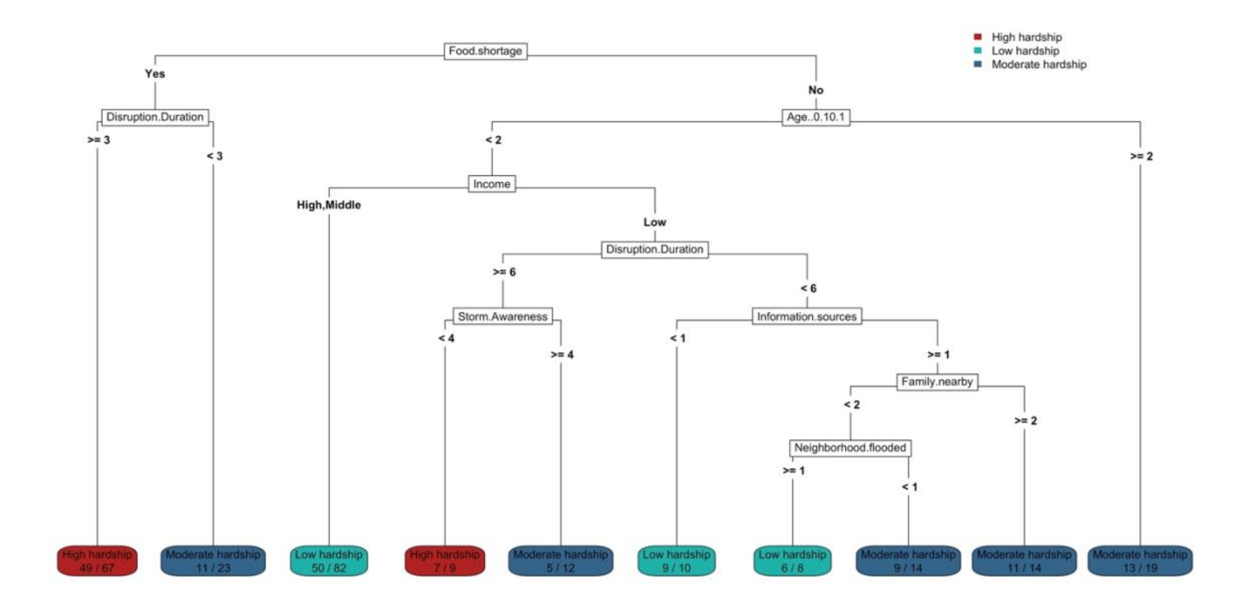


Food Infrastructure

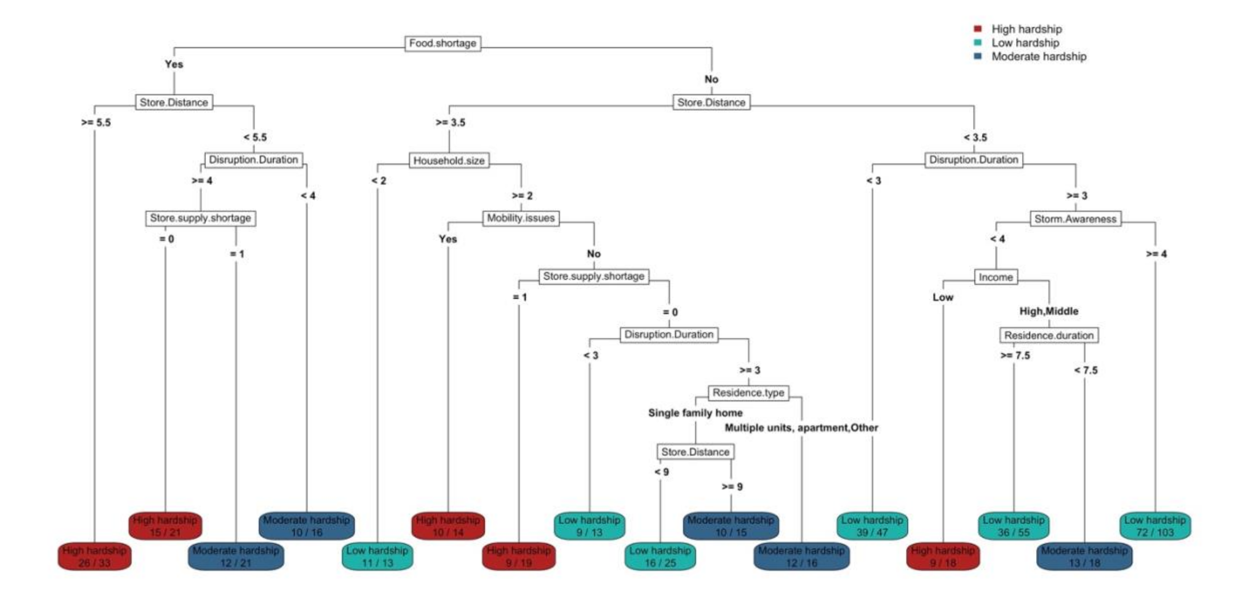
xiii. All groups



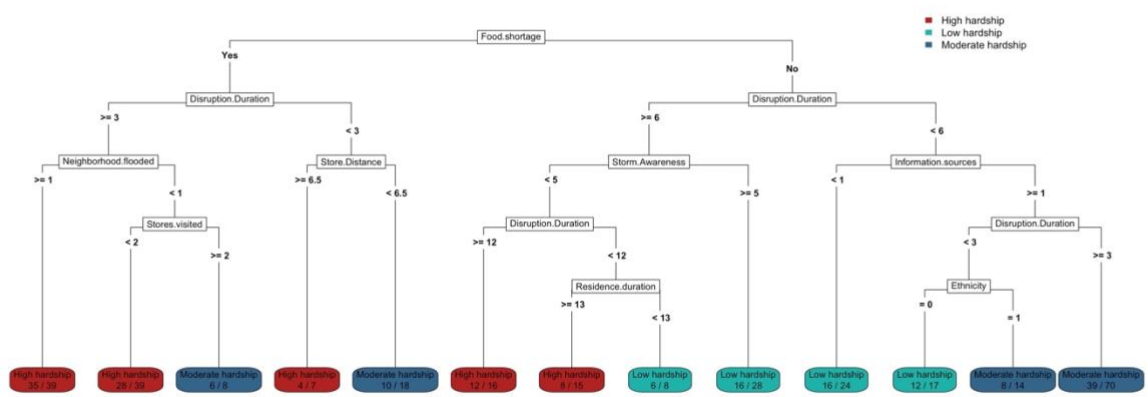
xiv. Minority



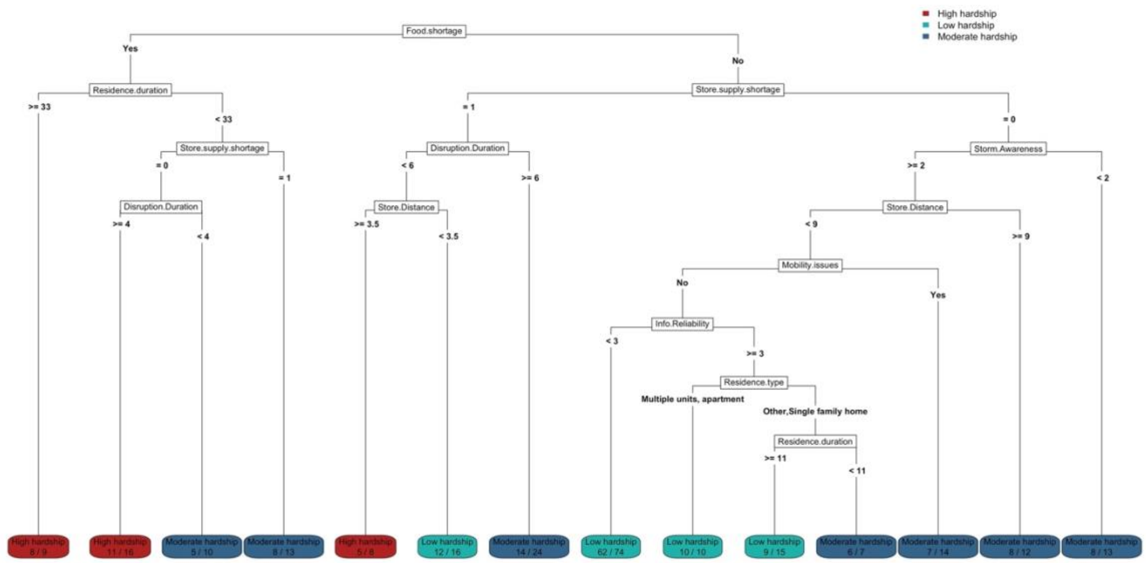
xv. White



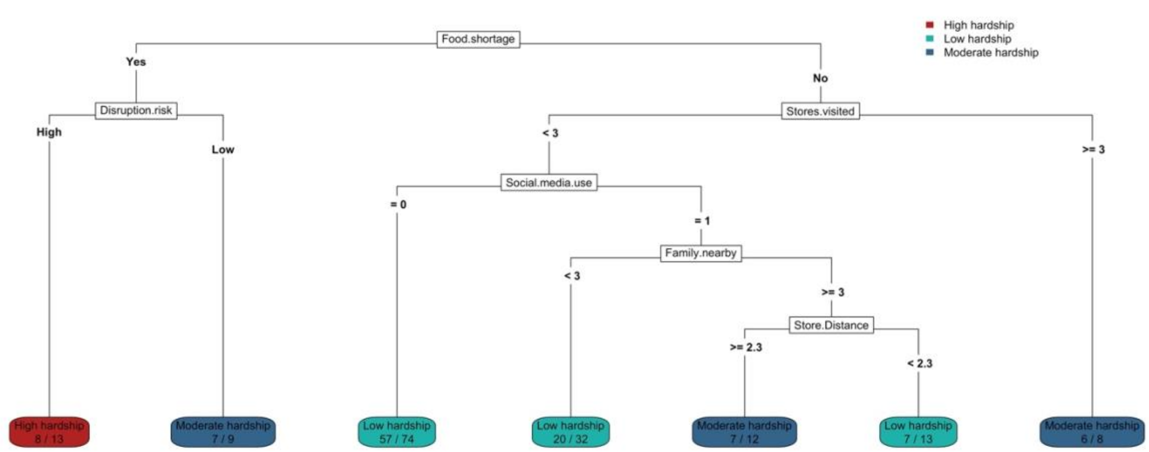
xvi. Low-Income



xvii. Middle Income

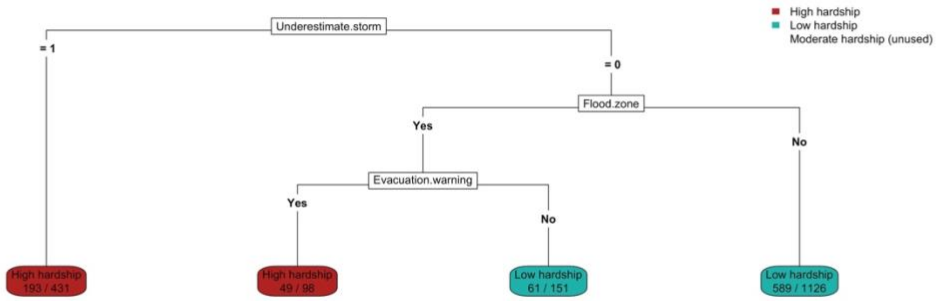


xviii. High Income

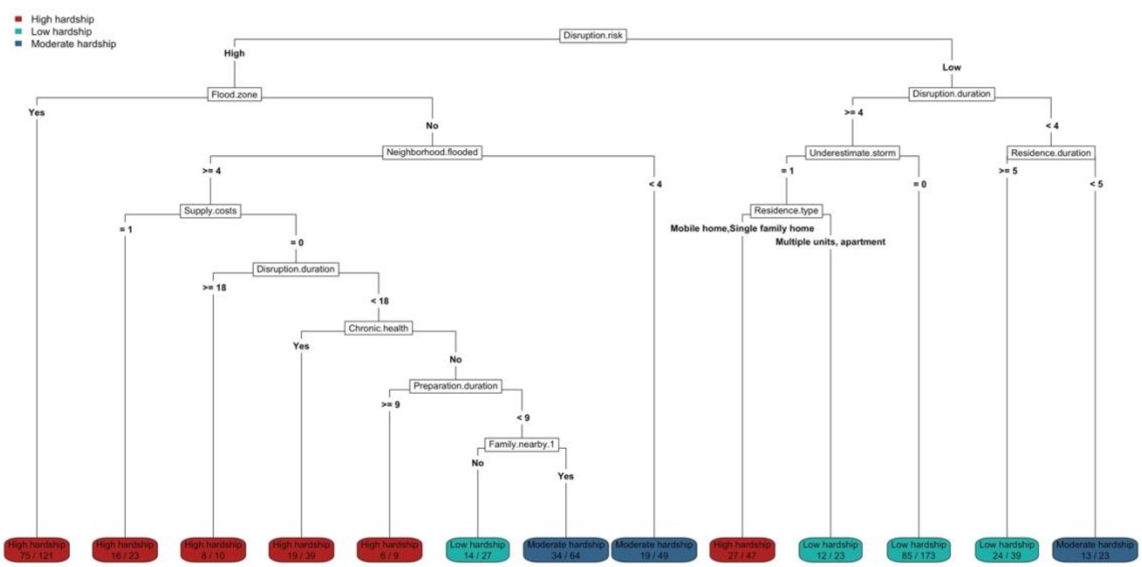


Road Infrastructure

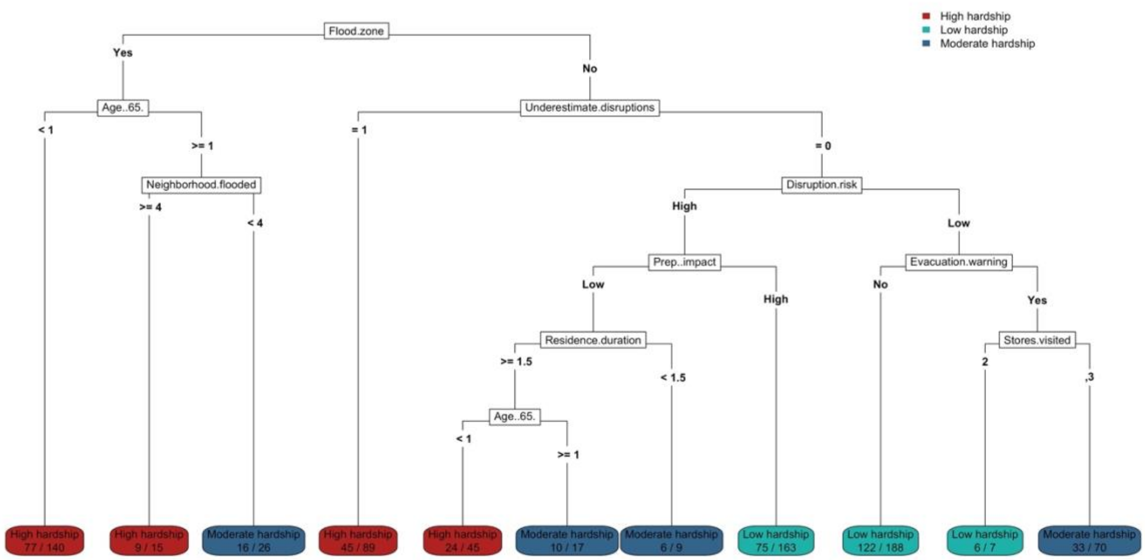
xix. All groups



xx. Minority

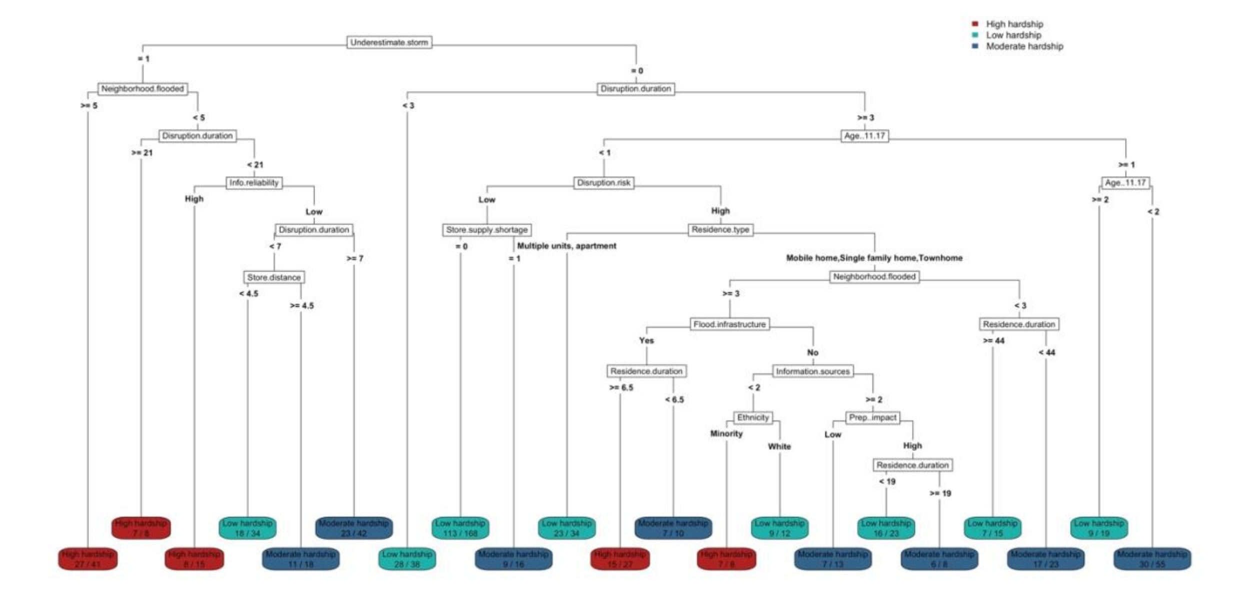


xxi. White

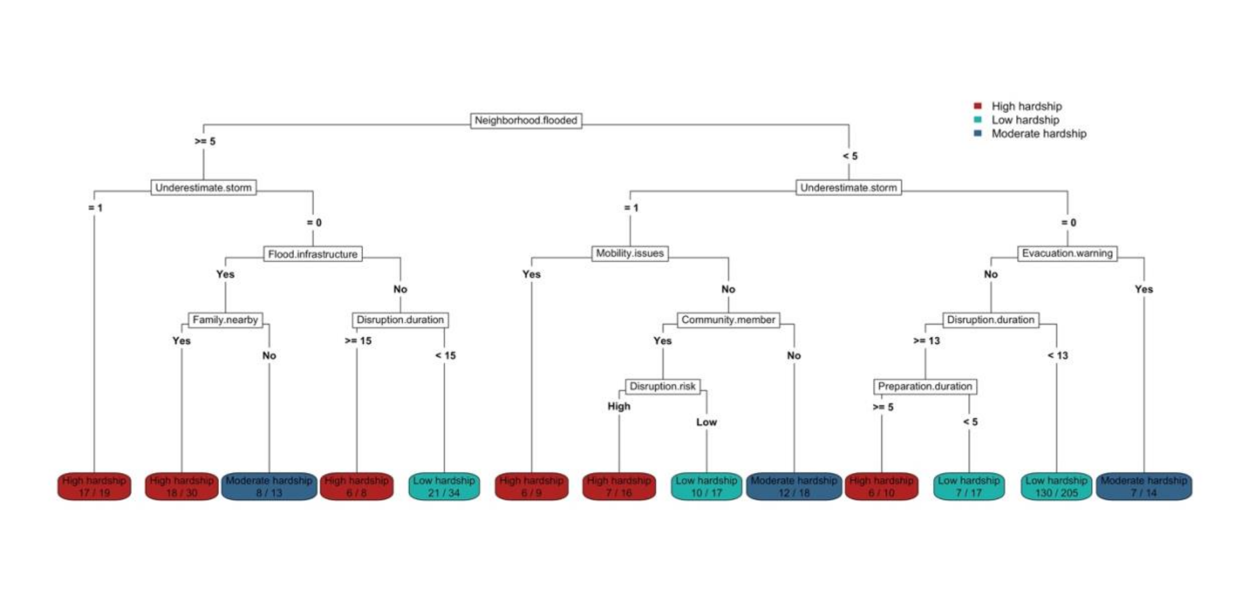


xxii. Low-Income

xxiii. Middle Income



xxiv. High Income



Household Survey Questions

Susceptibility

- Considering an upcoming severe hurricane, overall, how many days could your household tolerate the [infrastructure service disruptions]?

Sociodemographic Characteristics

- Income
    - Specify your household annual income from all sources before Hurricane [Harvey/Florence/Michael] landed.
- Education
    - What is the highest education level among your household members before Hurricane [Harvey/Florence/Michael] landed?
- Racial/ Ethnic Minority
    - Which of the following options would best describe your household's race and ethnicity?
- Children
    - How many people in your household were in the following age ranges before Hurricane [Harvey/Florence/Michael] landed, including yourself? [Less than 10 years old]
- Elderly
    - How many people in your household were in the following age ranges before Hurricane [Harvey/Florence/Michael] landed, including yourself? [65 years or older]
- Years of State Residence
    - How many years had you lived in [state] before Hurricane [Harvey/Florence/Michael] landed?
- Required Medications
    - Did any member of your household have a medical condition which required medications before Hurricane [Harvey/Florence/Michael] landed?
- Difficulty with Mobility/ Physical Disability
    - Did any member of your household have difficulties with mobility in satisfying the needs due to a physical health condition before Hurricane [Harvey/Florence/Michael] landed?
- Chronic Medical Condition
    - Did anyone in your household have a chronic medical condition before Hurricane [Harvey/Florence/Michael] landed?
- Owning a Vehicle
    - Did your household own a vehicle before Hurricane [Harvey/Florence/Michael] landed?

Property Factors

- Residence Type
    - What was the type of residence that you lived in before Hurricane [Harvey/Florence/Michael] landed?
- Home Ownership
    - What was your household's homeownership status before Hurricane [Harvey/Florence/Michael] landed?

- Distance to Supermarket
    - Approximately, what was the distance from the closest grocery store to your house before Hurricane [Harvey/Florence/Michael] landed?

- Location to Flood Zone
    - Before Hurricane [Harvey/Florence/Michael] landed, was your home located in a flood zone as designated by FEMA?

Risk Perception

- Evacuation (Filters)
    - Did your household evacuate? And if so, please specify when?
    - Did water enter your home, to the extent that you could not continue staying in your home during Hurricane [Harvey/Florence/Michael]?
    - Was your neighborhood flooded during Hurricane [Harvey/Florence/Michael]?
- Expectations
    - Before Hurricane [Harvey/Florence/Michael] landed, what was your expected duration (in number of days) of the following service interruptions?
- Days of Preparedness
    - How many days before landing, did your household start preparing for the upcoming event? (Please put your answer in the number of days)
- Length of Forewarning
    - How many days before landing, did your household first hear about Hurricane [Harvey/Florence/Michael]?
- Reliability of the information for each infrastructure service
    - During and immediately after Hurricane [Harvey/Florence/Michael], were you able to gather reliable information about the [infrastructure service disruptions]?

Previous Experience and Damage

- Previous Experience
    - Before Hurricane [Harvey/Florence/Michael] landed, did you have previous experience with any hurricanes, flooding, or any other types of disasters?
- Previous Loss
    - Before Hurricane [Harvey/Florence/Michael] landed, had you ever suffered any loss or damage from a disaster, either while living in your present home or a different place?

Resources

- Perception of Preparedness
    - Before Hurricane [Harvey/Florence/Michael] landed, what was your perception of your household's preparedness?
- Power Substitute
    - Did your household have any power back-up or substitute?
- Self-efficacy
    - Please consider your household's overall capabilities and select the degree of your agreement on the statement below:
    - I believe that through preparedness prior to a disaster, my household can completely cope with infrastructure service disruptions without experiencing the negative impacts on our well-being.

Social Capital

- Rely on Close Family/ Friends for Emergency in Nearby Areas
    - Before Hurricane [Harvey/Florence/Michael] landed, did you have relative or close friends in nearby areas to rely on their assistance in cases of emergencies?
- Rely on Close Family/ Friends for Emotional Well-Being
    - Before Hurricane [Harvey/Florence/Michael] landed, did you have any friends or relatives that you would feel free to talk about your emotional and mental well-being with?
- Member of a Community Organization
    - Before Hurricane [Harvey/Florence/Michael] landed, were you a member of a local community organization (neighborhood club, social club, place of worship, religious group, cultural group…)?
- Volunteer
    - Before Hurricane [Harvey/Florence/Michael] landed, have you ever volunteered in the social activities of your community?

Sensitivity

- Relative Need
    - How important was it for your household to have [the infrastructure service] access during Hurricane [Harvey/Florence/Michael]?