



Household Adaptations to and Impacts from Electric Power and Water Outages in the Texas 2021 Winter Storm

Nafiseh Soleimani¹; Rachel A. Davidson, A.M.ASCE²; James Kendra³;
Bradley Ewing⁴; and Linda K. Nozick⁵

Abstract: In February 2021, a winter storm brought snow, ice, and freezing temperatures, which caused severe interruptions in the electric power and water supply systems in Texas and surrounding areas. In this paper, we use survey data to investigate the ways that households adapted and reacted to those outages. The analysis aimed to determine (1) how common different household adaptations were, (2) how adaptations varied with outage and household characteristics, (3) how adaptations tended to occur together, (4) how unhappy households were as a result, (5) how household unhappiness varied with outage and household characteristics, and (6) what concerns influenced the unhappiness level. Results are compared with findings from a study that used an almost identical survey instrument but was based on a larger data set from Los Angeles. Findings from both studies suggest that almost everyone implemented at least one adaptation; most implemented several. They also agreed the most common adaptations were using candles, a flashlight, and/or a lantern; charging the cell phone in the car; purchasing bottled water; and delaying or reducing consumption. Both studies indicate that households experienced varied levels of unhappiness, which were similar for electric power and water interruptions. The reported levels of unhappiness were notably higher in Texas than Los Angeles, however, possibly because the outages had relatively long durations and were recent. Financial, time/effort, health, and stress concerns all were found to have a substantial influence on the extent of unhappiness, in both the Texas and Los Angeles analyses, suggesting that it is critical to consider all of them. Analysis of the Texas study introduced the new finding that repeated service outages during an event is associated with both increased adaptation implementation and greater unhappiness. Analyzing larger data sets from additional events in different locations would be helpful to further understanding of household experiences in service outages. DOI: [10.1061/NHREFO.NHENG-1742](https://doi.org/10.1061/NHREFO.NHENG-1742). © 2023 American Society of Civil Engineers.

Practical Applications: Several practical applications emerge from this work. First, by knowing how people are likely to adapt, officials can better prepare to support their constituents during a crisis. Anticipating the distribution of unhappiness could point infrastructure operators to consider other measures for service quality besides downtime alone, as important as that is. Knowing the differential effects of outages on different populations can improve officials' understanding of social vulnerabilities in their communities, which is needed for planning, education, and outreach. Electric and water outages accompany many kinds of hazard events; the extent to which a local population can adapt, and how officials and infrastructure operators can enhance those adaptations, will be important elements of local community resilience.

Introduction

Households rely on infrastructure system services for virtually all aspects of daily life. They use electric power for lighting, heating, and accessing electronic devices, for example, and potable water for drinking, bathing, and cleaning. When those services are interrupted, numerous negative consequences may follow in terms of health, safety, financial loss, and disruption of daily activities.

Thus, unsurprisingly, households typically try to lessen the negative impacts of service outages by adapting in many ways, planned and unplanned. They may purchase and use a power generator to adapt to an electric power outage, use water from a rain barrel during a water outage, or go to a hotel during a natural gas service interruption. In fact, these adaptations can represent a massive mediating influence on the effect of system outages. Recognizing the importance of such user adaptations and of understanding the implications of service outages for daily life, the study of resilience of infrastructure systems has expanded to include both ideas (NEHRP Consultants Joint Venture 2014; ATC 2016).

Nevertheless, quantitative empirical descriptions of household adaptations to and impacts from service outages are still limited. In this paper, we ask the same questions as Abbou et al. (2022) and Stock et al. (2023), but employ a different data set covering a different type of natural disaster. Whereas data in the current study describe actual behavior [revealed preferences (RP) data] during the February 10–21, 2021, winter storm centered in Texas, the previous studies were based on data from a larger sample of Los Angeles County residents that included a combination of (1) revealed preference responses from each respondent's longest outage experience (not necessarily a single event), and (2) questions about intended behavior [stated preference (SP)] in hypothetical future outages of specified durations. Both the Texas and Los Angeles

¹Graduate Student, Dept. of Civil and Environmental Engineering, Univ. of Delaware, Newark, DE 19711. Email: nafisehs@udel.edu

²Professor, Dept. of Civil and Environmental Engineering, Univ. of Delaware, Newark, DE 19711 (corresponding author). ORCID: <https://orcid.org/0000-0002-6061-5985>. Email: rdavidso@udel.edu

³Professor, Biden School of Public Policy and Administration, Univ. of Delaware, Newark, DE 19711. ORCID: <https://orcid.org/0000-0003-0888-1466>. Email: jmkendra@udel.edu

⁴Professor, Rawls College of Business, Texas Tech Univ., Lubbock, TX 79409. Email: Bradley.Ewing@ttu.edu

⁵Professor, School of Civil and Environmental Engineering, Cornell Univ., Ithaca, NY 14853. Email: lkn3@cornell.edu

Note. This manuscript was submitted on August 17, 2022; approved on May 23, 2023; published online on July 27, 2023. Discussion period open until December 27, 2023; separate discussions must be submitted for individual papers. This paper is part of the *Natural Hazards Review*, © ASCE, ISSN 1527-6988.

data sets, however, used the same questions about household adaptations to and impacts from electric power and water supply outages, allowing direct comparison of the results.

In this paper, we begin to examine the generalizability of the findings from those Los Angeles-based studies. In particular, we explore which findings are replicated in this new location for this new event, and which are not. We examine the following research questions (RQs):

- RQ1. How common are different types of household adaptations?
- RQ2. How does household adaptation implementation vary with (1) infrastructure type, (2) outage duration, (3) uses of the service, and (4) household characteristics?
- RQ3. Which household adaptations tend to occur together? Which tend not to?
- RQ4. How unhappy are households when service is interrupted?
- RQ5. How do household impacts vary with (1) infrastructure system type, (2) outage duration, and (3) household characteristics?
- RQ6. What are the concerns that influence a household's level of unhappiness associated with service interruptions?

Following a review of the related literature on household adaptations to and impacts from infrastructure system service outages, we describe the data and methods. The following sections address each of the six research questions in turn. We conclude with implications and limitations of this study.

Background

Household Adaptations to Service Outages

Although the study of adaptations to service outages includes those by businesses, government agencies, and nonprofit organizations, and adaptations to various types of events, here we focus on household adaptations to electric power and water service interruptions in particular. Previous studies have identified many examples of such adaptations, which we define as an action taken by the users of an infrastructure service to address their needs with other methods when that service is suspended or substantially reduced. Heidenström and Kvarnlöf (2018), for example, documented use of camping stoves to cook during electric power outages in winter storms in Norway and Sweden. Following the 2010 earthquake in Chile, some households got water from streams to replace water supply that was interrupted (Moreno and Shaw 2019). Similar examples have been observed in various extreme events and locations, resulting in a list of dozens of different adaptations (Abbou et al. 2022). The list of adaptations addressed in this paper was taken from this extensive literature review.

The literature has also proposed many variables that may help explain who implements what adaptations under what circumstances. These include variables describing (1) outage attributes (Zhang 2019), (2) past experiences and risk perception (Heidenström and Throne-Holst 2020; Clay et al. 2020; Martins et al. 2018; FEMA 2013), (3) sociodemographics (Osberghaus and Abeling 2022; Moreno and Shaw 2019; Ercumen et al. 2015; Jeandron et al. 2015; Dargin and Mostafavi 2020; Klinger et al. 2014), and (4) social connectedness (Wolf et al. 2010). Osberghaus and Abeling (2022) suggested that low-income households are extremely heat sensitive while having lower adaptive capacity than high-income households. Moreno and Shaw (2019) stated older people in Chile could locate ancient streambeds to draw water after experiencing the 2010 earthquake. When households experience water interruptions, they may rely on unsafe water alternatives, affecting their hygiene.

Despite these advances in knowledge, this body of work includes little quantitative study of the implementation of adaptations. This paper builds on the work of Abbou et al. (2022), which used a large survey-based data set that included both revealed and stated preference data to develop statistical models of adaptation implementation and provided evidence as to the generalizability of their findings.

Household Impacts from Service Outages

Efforts to identify and quantify household impacts of infrastructure system service interruptions can be partitioned into (1) needs-based, and (2) reaction-based (Davidson et al. 2022). In the former, a list of needs or uses the infrastructure system service helps a household, business, or organization meet are enumerated (e.g., survival, hygiene, earning income, and cooking), and the impact is defined in terms of the extent to which those are met. The needs may be defined more specifically or generally, and their definition may depend on the infrastructure system and location. Yang et al. (2021), for example, focused on individual physiological needs and incorporated adaptive capacity to evaluate the societal impact of disrupted water infrastructure, including a case study for Osaka, Japan. They defined five levels of need satisfaction, and then express societal impact as the percentage of the population in each. Tabandeh et al. (2018, 2019) use indicators to represent a person's capabilities, which capture distinct dimensions of an individual's well-being, including, for example, meeting physiological needs, earning income, being mobile, and being socially connected.

In reaction-based measures, the impact of the service disruption is captured in terms of the household's reaction to it, i.e., how they interpret the severity of the interruption and its implications (e.g., Dargin and Mostafavi 2020; Coleman et al. 2020; Esmalian et al. 2019). These methods typically implicitly include the effect of both any reduced level of service that exists even after adaptations and any (usually negative) experience associated with implementing the adaptations (e.g., money and time spent going to a hotel, or effort associated with using water from rain barrels).

Most studies using the micro approach have relied on self-reported measures in survey or interview data. Stock et al. (2023) developed two reaction-based measures of societal impacts—willingness to pay (WTP) to avoid service interruptions and a constructed scale of unhappiness. Focusing on electric power and water service interruptions, they use survey-based data from Los Angeles County, to fit regression models of WTP and unhappiness, both as functions of infrastructure type, outage duration, and household attributes. The current paper provides information as to the robustness of the findings from Stock et al. (2023).

Methods

Data Collection

Data were collected through a web-based survey coded in Qualtrics. The survey instrument, which was designed to capture households' experiences during the 2021 Texas winter storm, included questions related to (1) typical electrical and water uses, (2) interruptions in electricity and/or water service due to the storm (February 10–21), (3) adaptations undertaken to cope with and unhappiness associated with service interruptions, (4) risk attitudes, and (5) sociodemographics. The survey required an average of 7.5 min to complete.

The survey was distributed on Facebook in March–May 2021. Relevant groups and pages were chosen that focused on the storm and/or the affected area, including for example, “Disaster Response, Rescue, and Recovery Resources Network” and “Winter Storm 2021 Nacogdoches, Texas.” Members of the research team joined the pages, requested access to post or requested permission to post when necessary, and posted a link to the survey with an explanation of the study on each page. Institutional review board approval was obtained at the University of Delaware. The link was sharable once deployed. Three weeks after the initial posting, a comment was added to most posts to push them to the top of the page and inform potential respondents of the date the survey would close.

We posted the survey to 19 groups which collectively had 183,489 members, although members of those groups likely shared the post within their own social networks. There were 215 useable responses. Benefits of this method of survey deployment, previously used by Farmer and DeYoung (2019), DeYoung et al. (2019), and Mongold et al. (2021), include that it can be done quickly, maximizing the accuracy of recollections, and it is less expensive to deploy and analyze than mail or phone surveys.

To examine the representativeness of the sample, demographic data for the sample were compared with that for the population from which they were drawn. Population demographics were computed using county-level data from the US Census (US Census Bureau 2019), weighted based on the number of respondents from each county. Overall, the sample is reasonably similar to the population, with a few exceptions. The sample included more White people (85% in sample versus 65% in the population), more females (80% sample versus 56% population), and more with at least a 4-year degree (58% in sample versus 35% in the population). The sample and population had similar age and income distributions (average age was 50 in the sample and 45 in the population; the average household income was \$102,000 in sample and \$97,000 in the population).

Data Summary

Household Societal Impact, Adaptation, and Outage Duration Variables

Questions were included to solicit information about the durations of electricity and water outages respondents experienced (four for electricity and four for water). The questions and answer choices were as follows:

- Q1: Did you experience a loss of electricity [water service] at your residence at any time from February 10 to February 21, 2021? Possible answers respondents could pick were Yes, it went off and on more than once; Yes, it went off just once; and No.
- Q2: Over approximately how much time was your electricity [water] disrupted during that period (i.e., from the first time it was interrupted until the last time it came back on)? Respondents were asked to enter the number of full days and number of hours.
- Q3: Approximately how long did the longest electricity [water] outage during that period last?
- Q4: Approximately how long did the electricity [water] outage last?

For each infrastructure type, if the answer to Q1 was Yes, it went off and on more than once, Q4 was not asked; if the answer to Q1 was Yes, it went off just once, Q2 and Q3 were not asked; and if the answer to Q1 was No, Q2, Q3, and Q4 were not asked.

For those who experienced an outage, additional questions were asked about how they adapted to those outages and the impacts of

them. For each outage (electricity and/or water), the following questions were asked:

- Q5: Which of the following did you do, if any, to meet your household electricity [water] needs during the longest outage that you experienced? (Select all that apply).
A list of adaptations was provided for them to select. For electricity and water, respectively, the 19 and 15 adaptations applicable to the infrastructure type given in Table 1, developed based on an extensive literature review, were listed.
- Q6: Considering the actions you took to deal with the longest outage that you experienced, as well as any remaining reduction in service, what level of unhappiness did you feel as a result of the outage? The answers respondents could choose from were Not unhappy; Slightly unhappy; Moderately unhappy; Very unhappy; and Extremely unhappy.
- Q7: To what extent did each of the following concerns influence your level of unhappiness? For each of four concerns—Financial cost, Time or effort to meet household needs, Physical health effects, and Stress—there were four choices: Not at all, To a minor extent, To a moderate extent, and To a major extent.

Other Explanatory Variables

Tables 2 and 3 provide summary statistics for the categorical and continuous explanatory variables in the Texas survey, respectively, with a comparison with data from the Los Angeles survey. The explanatory variables can be grouped in five main categories:

- (1) outage attributes (x_{type} , $x_{e.num}$, $x_{w.num}$, x_{notice} , and x_{damage}),
- (2) type of service usage ($x_{e.dev}$, $x_{e.work}$, $x_{e.source}$, $x_{w.dev}$, $x_{w.work}$, and $x_{w.source}$),
- (3) past experiences and risk perception ($x_{l.emer}$, $x_{w.emer}$, and $x_{n.emer}$),
- (4) sociodemographics (x_{gen} , x_{race} , x_{edu} , x_{child} , x_{elder} , x_{pets} , $x_{med.c}$, $x_{med.e}$, x_{own} , x_{house} , x_{employ} , and $x_{marital}$),
- and (5) social connectedness ($x_{neighbor}$).

To examine the possible effects of repeated outages ($x_{e.num}$ and $x_{w.num}$) and outage duration ($x_{e.dur}$ and $x_{w.dur}$), respondents were asked questions Q1, Q3, and Q4, respectively. When a respondent experienced more than one outage (i.e., the power went off and on), the outage duration was taken to be the longest outage duration (Q3). Respondents also answered the questions “Did you receive prior notice of the blackouts? Yes or No” and “Did you experience any property damage as a result of any disruption of electricity or water? Yes or No” to collect data for the prior notice (x_{notice}) and property damage (x_{damage}) variables.

Respondents were asked in what ways they regularly use electricity and water. Of nine possible choices for each, we assumed using the services for medical devices and work purposes are of primary importance, and thus included only those uses ($x_{e.dev}$, $x_{e.work}$, $x_{w.dev}$, and $x_{w.work}$). To determine if someone might have a backup source of electric power or water, we asked “Which of the following energy [water] sources does your household use at your place of residence? (Select all that apply)” and coded responses as one source or multiple sources ($x_{e.source}$ and $x_{w.source}$).

Three variables were used to capture prior hazard event experiences and risk perception as possible predictors of adaptation to and impact of service outages. Respondents were asked “How likely do you think it is that you and your household will be impacted by emergencies in the next five years?” ($x_{l.emer}$); “How worried are you about the potential threat of you and your household being impacted by emergencies in the next five years?” ($x_{w.emer}$); and “Other than the February 2021 winter storm, have you ever experienced other emergencies that caused some negative impact on your life?” ($x_{n.emer}$). In all three cases, the responses were coded as binary due to the relatively small sample size, as indicated in Table 2. This Preparation (x_{prep}) variable was coded as the number of preparation-based activities respondents took out of

Table 1. Number of responses for each adaptation

Adaptation		Electric power		Water supply	
Yes	No	Yes	No	Yes	No
y_{gen}	Other	24	130	N/A	N/A
y_{candle}	Used candles, flashlight, and/or lantern	130	24	N/A	N/A
y_{heater}	Used a nonelectric heater and/or fireplace	54	100	N/A	N/A
y_{stove}	Used a gas stove for warmth	24	130	N/A	N/A
y_{stove}	Used a gas stove and/or camping stove to cook meals and/or boil water	52	102	N/A	N/A
y_{car}	Charged cell phone in the car	77	77	N/A	N/A
y_{carw}	Used car for warmth	42	112	N/A	N/A
y_{shop}	Charged cell phone, laptop, and/or tablet at work and/or in a coffee shop	16	138	N/A	N/A
y_{wifi}	Used Wi-Fi somewhere other than home	5	149	N/A	N/A
y_{burn}	Burned furniture, driftwood, yard trimmings, or other fuels	9	145	N/A	N/A
y_{center}	Went to a warming center	3	151	N/A	N/A
y_{lake}	Used water from lakes, rivers, and/or creeks	N/A	N/A	2	85
y_{govt}	Used water delivered by the government	N/A	N/A	2	85
y_{comm}	Used water provided by community or neighborhood-based organizations	N/A	N/A	11	76
y_{tank}	Used water from private tank and/or rain barrel	N/A	N/A	4	83
y_{pool}	Used water from a swimming pool	N/A	N/A	3	84
y_{tub}	Used water stored in the bathtub	N/A	N/A	36	51
y_{snow}	Melted snow or ice	N/A	N/A	37	50
y_{bottle}	Purchased bottled water	N/A	N/A	70	17
y_{red}	Reduced consumption of electricity [water] (e.g., cooked less)	71	83	54	33
y_{delay}	Delayed consumption of electricity [water] (e.g., postponed laundry)	86	68	53	34
y_{visit}	Visited a relative's or friend's house for their heat [water]	29	125	15	72
y_{rel}	Stayed at a relative's or friend's house	33	121	23	64
y_{hotel}	Moved to a hotel	7	147	3	84
y_{town}	Traveled out of town	2	152	4	83
y_{other}	Other	10	144	7	80

12 possible activities—preparing an evacuation plan, preparing a household reunion plan, searching for preparation information, storing important documents, keeping extra medication, keeping extra cash, gathering emergency numbers, storing 3 days of water per person, storing nonperishable food and snacks, storing first aid supplies, storing flashlights, and storing a battery-operated radio.

To elicit the level of social connectedness households feel, we asked “Thinking about your neighborhood, how much do you agree or disagree with each of the following sentences: (1) ‘People in this neighborhood are willing to help neighbors’ (Sampson et al. 1997), (2) People in this neighborhood know each other well, (3) ‘People in this neighborhood can be trusted’ (Sampson et al. 1997), (4) People in this neighborhood participate in neighborhood organizations, and (5) ‘My neighborhood is a safe place’” (Merrin et al. 2015). The possible choices were Strongly disagree, Disagree, Agree, and Strongly agree. We computed the neighbor connectedness variable (x_{neigh}) by assigning values of one to four to each response choice, respectively, averaging the answers for the five statements, and coding them as zero for Does not feel connected (≤ 2.5), and one for Feels connected (> 2.5).

Imputation

After removing the 51 respondents who did not experience either an electric power or water outage and respondents who had answered fewer than 70% of the survey questions, we had 164 respondents with a total of 241 observations (154 respondents with only an electricity outage, 87 with only a water outage, and 77 with both). The data in Tables 1 and 2, however, still included missing values. Common methods of handling missing data—listwise and pairwise deletion—discard useful data and result in coefficient estimates that are potentially biased (Harrell 2015). Therefore, we used multiple imputation, which avoids the problems of deletion methods and, unlike single imputation, accounts for the

uncertainty introduced by the fact that missing values are being imputed and so as to not underestimate the p -values (van Buuren 2012; Harrell 2015). In this approach, the data set was imputed multiple times creating m complete data sets. The analysis was conducted separately on each, and then the results were combined (van Buuren 2012).

Specifically, we used the {mice} package in R version 4.0.5 (R Core Team 2022), which implements the multivariate imputation using chained equations (MICE) algorithm (van Buuren and Groothuis-Oudshoorn 2011; van Buuren 2012). We generated 50 imputed data sets, consistent with approximate guidelines from van Buuren (2012) and Harrell (2015). Default settings were used—logistic regression for binary variables, proportional odds for ordered, and Bayesian linear regression for continuous variables. We checked to ensure the distributions of the observed and imputed data sets were sufficiently similar, using kernel densities for continuous variables, and histograms for binary variables. Results of all checks suggest that the imputed data sets matched the observed data well in terms of distributions of variables. Results from the imputed data sets were combined using Rubin’s rules (van Buuren 2012).

Comparison with Los Angeles County Data

Results of the analysis of the Los Angeles data from Abbou et al. (2022) and Stock et al. (2023) offer a valuable comparison for the results of this study. To facilitate interpretation of those comparisons, we summarize the key differences in Table 4; other variables were similar. The questions in the Los Angeles survey were the same as those described in the “Data Summary” section, with a few minor differences. As noted in Table 2, the Los Angeles survey did not include the questions associated with the multiple interruptions ($x_{e,num}$ and $x_{w,num}$), prior notice (x_{notice}), and property damage (x_{damage}), or the following adaptations: Used your gas stove for

Table 2. Number of respondents associated with each level of categorical variables

			No. of respondents	
Variable	Description	Levels	Texas ^a	LA
Outage attributes				
x_{type}	Infrastructure service type	0: Electric	164	1,615
		1: Water	164	1,615
$x_{e,num}$	More than one power interruption	0: One interruption	42	N/A
		1: More than one interruption	112	N/A
$x_{w,num}$	More than one water interruption	0: One interruption	45	N/A
		1: More than one interruption	42	N/A
x_{notice}	Prior notice	0: Not received	110	N/A
		1: Received	44	N/A
x_{damage}	Property damage	0: No	114	N/A
		1: Yes	50	N/A
Type of service usage				
$x_{e,dev}$	Use electricity for medical devices	0: No	139	1,474
		1: Yes	25	141
$x_{e,work}$	Use electricity for work	0: No	57	1,205
		1: Yes	107	410
$x_{e,source}$	Multiple sources of energy	0: No	55	418
		1: Yes	109	1,197
$x_{w,dev}$	Use water for medical devices	0: No	151	1,520
		1: Yes	13	95
$x_{w,work}$	Use water for work	0: No	134	1,483
		1: Yes	30	132
$x_{w,source}$	Multiple sources of water	0: No	109	824
		1: Yes	55	791
Past experiences and risk perception				
$x_{l,emer}$	Perceived likelihood of emergency in next 5 years	0: Very unlikely, unlikely, not sure	20	515
		1: Likely or very likely	142	1,100
$x_{w,emer}$	Worry about emergency in next 5 years	0: Not at all or slightly worried	55	885
		1: Moderately or extremely worried	106	730
$x_{n,emer}$	Has experienced a negative emergency	0: Had not had negative experience	63	1,134
		1: Has had a negative experience	95	481
Sociodemographics				
x_{gen}	Gender	0: Female	117	838
		1: Other	28	777
x_{race}	Race	0: White	126	428
		1: Other	21	1,187
x_{edu}	Education	0: <4-year degree	47	1,155
		1: 4-year degree+	65	460
x_{child}	Children (<18 years) live in household	0: No	40	918
		1: Yes	55	692
x_{elder}	Elders (65 + years) live in household	0: No	46	1,176
		1: Yes	30	434
x_{pets}	Pets live in household	0: No	29	612
		1: Yes	120	1,003
$x_{med.c}$	Anyone with a medical condition in household	0: No	110	1,167
		1: Yes	35	448
$x_{med.e}$	Anyone in household relies on medical equipment	0: No	123	1,426
		1: Yes	23	189
x_{own}	Homeownership	0: Do not own	44	788
		1: Own	100	827
x_{house}	House type	0: Single-family, duplex, townhome	116	1,061
		1: Other	29	554
x_{employ}	Employment status	0: Not traditionally employed	53	720
		1: Employed full-time or part-time	93	895
$x_{marital}$	Marital status	0: Not married	57	928
		1: Married	89	687
Social connectedness				
$x_{neighbor}$	Feels connection to neighborhood	0: Does not feel connected	43	572
		1: Feels connected	108	1,043

Note: N/A = not asked in survey.

^aNot all variables have 164 responses due to missing data.

Table 3. Descriptive statistics for continuous variables for Texas and LA

Variable	Description (unit)	No. of responses		Mean		Standard deviation	
		Texas	LA	Texas	LA	Texas	LA
$x_{e,dur}$	Outage duration, electricity (h)	122	1,302	62.20	18.88	41.64	81.29
$x_{w,dur}$	Outage duration, water (h)	48	522	101.01	25.41	52.76	99.61
x_{prep}	Preparation ^a	155	1,615	7.69	7.01	2.93	3.38
x_{age}	Age (years)	135	1,611	45.11	41.96	14.01	16.40
x_{inc}	Income ^b (thousands of USD)	135	1,615	101.90	77.47	67.78	65.33
$x_{yr,h}$	Years living at current address	139	1,590	10.35	14.20	9.85	12.50
$x_{yr,c}$	Years living in your current county	139	1,600	19.89	31.12	14.87	17.78

^aPreparation is a continuous value from 0 to 12.

^bIncome was asked as an interval variable but was coded as a continuous variable with the values in parentheses for each interval: less than \$15,000 (\$7,500), \$15,000–\$35,000 (\$25,000), \$35,000–\$50,000 (\$42,500), \$50,000–\$75,000 (\$62,500), \$75,000–\$100,000 (\$87,500), \$100,000–\$150,000 (\$125,000), \$150,000–\$250,000 (\$200,000), and more than \$250,000 (\$300,000).

Table 4. Key differences between Texas and Los Angeles County data sets

Survey feature		Texas	Los Angeles County
Survey type		Web-based deployed March 21–May 21	Web-based deployed May 20–December 20
Sample type and location		Convenience sample identified through social media (66% in Texas)	Census-representative quota-based sample with all respondents from LA County
Number of responses		241	1,615
Type of data		RP related to winter storm of February 2021	RP from each respondent's longest outage experience (not a single event) and SP for hypothetical outages of specified durations (1 day, 3 days, 1 week, and 1 month)
Outage durations (h)		Electric: mean = 62; standard deviation = 42 Water: mean = 101; standard deviation = 53	RP Electric: mean = 19; standard deviation = 81 Water: mean = 25; standard deviation = 100 SP Electric: mean = 240; standard deviation = 283 Water: mean = 240; standard deviation = 283
Respondent demographics		81% are female 86% are White 61% are married 42% have <4-year degree 81% have pets in the household \$102,000 mean annual income	52% are female 27% are White 43% are married 72% have <4-year degree 62% have pets in the household \$77,000 mean annual income
Risk perception/experience		66% worry about emergency in next 5 years 60% experienced a negative emergency	45% worry about emergency in next 5 years 30% experienced a negative emergency
Use of service		65% use electricity for work	25% use electricity for work

warmth ($y_{stove,w}$), Used your car for warmth ($y_{car,w}$), Melted snow or ice (y_{snow}), and Used water provided by community or neighborhood-based organizations ($y_{stove,w}$). In some cases, the RP and SP questions in the Los Angeles data exhibit different behavior; in those cases, the results are separated into LA-SP and LA-RP.

Analyses and Results

Adaptation Adoption Frequency

The first research question asks how common the different types of household adaptations are. Although all those examined in this study have been observed in previous events, little is known about how common each is in general. We first address this question by examining adaptation implementation by respondent. Fig. 1 shows histograms of the number of adaptations each respondent implemented for the electric power and water supply outages,

and for the Texas data, as well as the Los Angeles data, the revealed and stated preference data for comparison.

They indicate that the use of multiple adaptations is very common for both electric power and water. The Texas data indicate that each respondent implemented an average of 12 adaptations for electric power and 10 for water. The Los Angeles data suggest fewer adaptations per person, but still multiple, with average of seven and five for electric power and water in the SP data, respectively, and two and two for electric power and water in the RP data, respectively.

To determine how common specific adaptations are, we examine Figs. 2(a and b), which show the percentage of respondents who did each adaptation for electric power and water, respectively. For electric power, the most common adaptation in Texas (of those in the survey) was using candles, flashlight, and/or lantern (84%). As Fig. 2(a) illustrates, other very common adaptations were delaying consumption (56%), charging the cell phone in the car (50%), and reducing consumption (46%). These were also the four most common electric power adaptations in the Los Angeles data set,

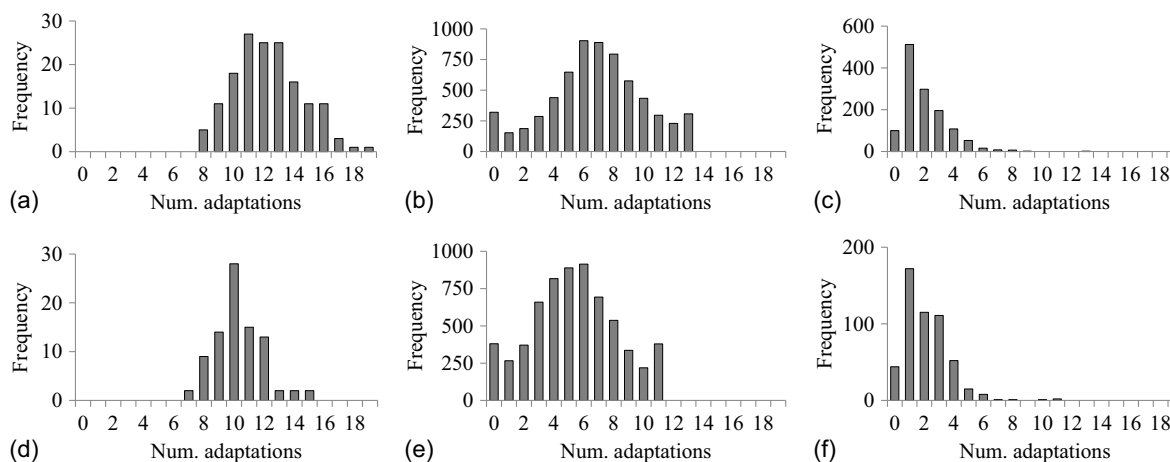


Fig. 1. Histograms of the number of adaptations implemented by each respondent for (a) Texas electric power; (b) LA SP electric power; (c) LA RP electric power; (d) Texas water; (e) LA SP water; and (f) LA RP water.

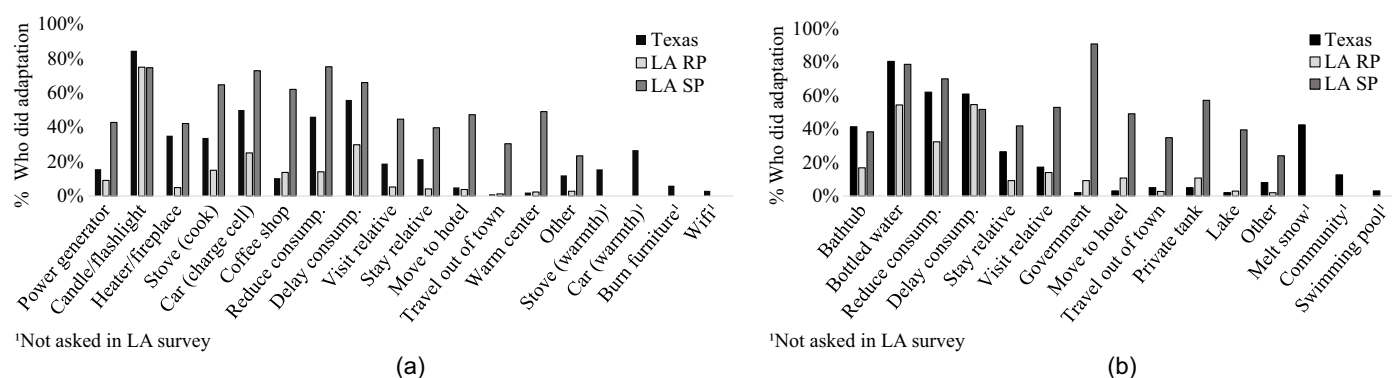


Fig. 2. (a) Percentage of respondents who said they did/would do each electric power adaptation in Texas, Los Angeles (RP), and Los Angeles (SP); and (b) percentage of respondents who said they did/would do each water adaptation in Texas, Los Angeles (RP), and Los Angeles (SP).

although the percentages of people saying they had implemented them in the Los Angeles RP data were smaller, perhaps because the outage durations were shorter in the Los Angeles RP data, as indicated in Table 4.

The least common electric power adaptations in both Texas and the Los Angeles RP included going to a coffee shop (10%), a hotel (5%), out of town (1%), or to a warming center (2%). Although the most common tended to be relatively inexpensive, the least common involved travel. Notably, for almost all adaptations, the frequency of implementation in the Texas data fell between the lower percentage in the Los Angeles RP data and the higher percentage in the Los Angeles SP data.

For water supply, the most common adaptations in Texas were purchasing bottled water (80%), reducing consumption (62%), and delaying consumption (61%), as noted in Fig. 2(b). These were also the most common in the Los Angeles data set, with similar percentages for the SP data and somewhat lower for the RP data. Given the importance of bottled water, policies may focus on logistics and distribution. Among the least common water adaptations in Texas—all implemented by fewer than 13% of respondents—were using water from the government, community organization, a private tank, or a lake; or traveling to a hotel or out of town. Those adaptations were also uncommon in the Los Angeles RP data, but they were quite common in the Los Angeles SP data. This could be due to the fact that it was stated preference data or due to the longer outage durations associated with the

Los Angeles SP data. Like with electric adaptations, although the most common tended to be relatively inexpensive and easy to implement, the least common involved travel, help from other people, and/or access to a special resource (e.g., a lake). Melting snow was quite common in the Texas data (43%) because this event was a winter storm. It was not asked in the Los Angeles survey, but would likely not be as common there due to the rarity of snow in that region.

Predictors of Adaptation Adoption

We used chi-square contingency tests and one-way ANOVA to identify possible relationships between adaptation decisions (binary variable) and each explanatory variable. The use of these nonparametric tests provides useful information given the relatively smaller sample size than that of Abbou et al. (2022), who utilized logistic multiple regression. In fact, given that households experienced far fewer water outages than power outages, we found little evidence of relationships between the explanatory variables and implementation of any water adaptations. Thus, in the interest of brevity, except for $x_{w,num}$, results for water adaptations are not presented here, but are available from Soleimani (2022).

Outage Attributes

Results in Table 5 suggest that the longer an electric power outage duration, the more likely someone is to implement the following

Table 5. P -values of χ^2 tests for electric power adaptations versus explanatory variables

Test type	Variable	Adaptive strategy											
		Power generator	Candle/ flashlight	Heater/ fireplace	Stove (cook)	Car (charge cell)	Coffee shop	Reduce consumption	Delay consumption	Visit relative	Stay relative	Stove (warmth)	Car (warmth)
Chi-square test results	Number of interruption, $x_{e.numint}$	0.60	0.01 ^a	0.05 ^a	0.79	1.00	0.94	0.01 ^a	0.01 ^a	0.46	0.83	0.98	0.90
	Prior notice, x_{notice}	1.00	0.25	1.00	0.37	0.86	0.53	0.43	1.00	0.42	0.20	1.00	0.62
	Property damage, x_{damage}	1.00	0.80	1.00	0.62	0.08	0.10	0.53	1.00	0.36	0.22	0.81	0.01 ^a
	Medical devices, $x_{e.dev}$	0.23	0.96	1.00	1.00	0.65	1.00	1.00	0.45	0.63	0.43	0.23	0.75
	Work, $x_{e.work}$	0.33	1.00	0.58	0.24	1.00	0.24	<0.001 ^a	<0.001	0.04 ^b	0.39	1.00	0.27
	Energy source, $x_{e.source}$	0.89	1.00	<0.001 ^a	<0.001 ^a	<0.001	1.00	0.85	0.88	0.36	0.11	<0.001 ^b	0.64
	Likely emergency, $x_{l.emer}$	0.67	0.32	0.01 ^b	1.00	0.81	0.21	0.94	1.00	0.30	0.10	1.00	0.34
	Worry, $x_{w.emer}$	0.41	0.41	0.13	0.02 ^b	0.46	0.03 ^b	0.86	0.61	0.32	0.05	0.73	0.05
	Negative impact, $x_{n.emer}$	0.16	0.22	0.30	0.61	0.59	0.40	0.84	0.90	0.21	0.03	1.00	0.99
	Gender, x_{gen}	0.94	0.38	0.80	0.78	0.39	1.00	1.00	0.69	0.95	1.00	0.92	0.98
	Race, x_{race}	0.20	0.29	0.23	0.74	0.17	0.62	0.45	0.51	0.72	0.87	1.00	0.22
	Education, x_{edu}	0.63	0.78	0.25	0.01 ^b	1.00	1.00	0.41	0.78	0.20	0.98	0.23	0.40
	Children, x_{child}	0.40	0.78	0.99	0.57	0.54	0.42	0.46	0.90	0.66	0.92	0.60	0.74
	Elders, x_{elder}	0.33	0.06	0.03 ^b	0.06	0.41	1.00	<0.001 ^b	0.05	0.12	0.78	0.91	0.25
	Pets, x_{pets}	0.93	0.24	0.04 ^b	0.69	0.83	0.99	0.11	0.02 ^a	0.62	0.55	0.71	0.81
	Medical condition, $x_{med.c}$	0.74	1.00	1.00	0.23	0.88	0.65	0.88	0.70	0.12	0.44	0.93	0.08
	Medical equipment, $x_{med.e}$	0.71	1.00	0.96	1.00	0.16	0.63	0.87	1.00	0.55	1.00	1.00	0.09
	Ownership, x_{own}	0.02 ^b	0.41	<0.001 ^b	0.03	0.02	0.25	0.46	0.47	0.03 ^b	0.08	0.45	0.13
	House type, x_{house}	0.08	0.54	0.04 ^a	0.02 ^a	0.01 ^a	0.03 ^a	0.86	0.72	<0.001 ^a	<0.001 ^a	0.78	<0.001 ^a
	Employment, x_{employ}	1.00	0.64	0.36	0.89	0.42	0.91	1.00	1.00	0.25	0.40	0.86	0.32
	Marital, $x_{marital}$	0.03 ^a	0.29	<0.001 ^a	<0.001	0.17	0.84	0.75	0.79	0.30	0.67	0.48	0.20
	Neighbor connection, $x_{neighbor}$	0.15	0.07	0.04 ^a	0.98	0.36	0.24	0.61	0.29	0.67	0.53	0.40	0.04 ^b
ANOVA test results	Outage duration, $x_{dur,e}$	0.15	<0.001 ^a	<0.001 ^a	1.00	<0.001 ^a	0.26	0.13	0.39	0.31	<0.001 ^a	0.97	0.02 ^a
	Preparation, x_{prep}	<0.001 ^a	<0.001	1.00	0.47	0.85	0.16	0.43	0.82	0.13	0.18	0.78	0.60
	Age, x_{age}	0.61	0.04 ^b	0.08	0.54	0.56	0.74	0.02 ^b	<0.001 ^b	0.09	0.01 ^b	0.07	0.15
	Income, x_{inc}	0.38	0.56	<0.001 ^b	0.38	0.72	0.25	0.13	0.77	0.99	0.79	0.61	0.60
	Years in house, $x_{yr,h}$	<0.001 ^a	0.01 ^b	0.70	0.95	0.25	0.99	0.06	0.18	0.07	0.07	0.28	0.10
	Years in county, $x_{yr,c}$	0.02 ^a	0.05 ^b	0.94	0.81	0.44	0.68	0.15	0.06	0.19	0.79	0.05	<0.001 ^b

^aFor variables at significance level = 0.05, direct effect.^bFor variables at significance level = 0.05, negative effect.

adaptations: Candle/flashlight (y_{candle}), Heater/fireplace (y_{heater}), Car (charge cell) (y_{car}), Stay with a relative (y_{rel}), and Car (warmth) (y_{carw}). This agrees with the conclusion about Stay with a relative (y_{rel}) in the Los Angeles data. However, by contrast, the Los Angeles data suggest that Candle/flashlight (y_{candle}) and Car (charge cell) (y_{car}) were less common as outage duration increased, perhaps because households found other charging alternatives, which may not have been available in the cold temperatures and difficult travel conditions of the Texas winter storm.

As indicated in Table 5, whether an interruption occurred once or more than once ($x_{e,\text{num}}$) was one of the variables most related to implementation of adaptations. Candle/flashlight (y_{candle}), Heater/fireplace (y_{heater}), Reduce consumption (y_{red}), and Delay consumption (y_{delay}) were all more likely for respondents who experienced more than one outage than those who experienced just one. This type of cumulative effect is consistent with searching for the optimal mix of adaptations to deal with their situation. Respondents who experienced more than one water outage were more likely to implement all adaptations except Used water provided by community or neighborhood-based organizations (y_{comm}). For the Visit relative adaptation (y_{visit}), the p -value is 0.04; for all others, it was <0.001. The Los Angeles survey did not ask about multiple interruptions.

Types of Service Usage

Table 5 indicates evidence ($p < 0.001$) that people who use electric power in their home for work or business purposes ($x_{e,\text{work}}$) were more likely to adapt by reducing consumption (y_{red}) than those who do not. Examining the data more directly showed a 0.57 probability of reducing consumption for someone who uses power for work, versus a 0.27 probability for someone who does not. A similar relationship was seen in the Los Angeles data. This may indicate that those who work from home have more flexibility in how they allocate their time and resources than those who must leave the house to go to work.

There is also evidence that people who have more than one source of energy in their home ($x_{e,\text{source}}$) were more likely to use a nonelectric heater and/or fireplace (y_{heater}) or gas stove and/or camping stove (y_{stove}) and less likely to use a gas stove for warmth (y_{stovew}). The first two relationships make sense because one can only use gas-powered adaptations if one has gas service to the house. Because electric power is the main energy source, those with more than one energy source typically have something in addition to that, often natural gas. The Los Angeles data provided similar evidence for y_{stove} but not y_{heater} .

Past Experiences and Risk Perception, Sociodemographics, and Social Connectedness

Among the relationships for which the Texas data offer evidence, the most statistically significant ones ($p < 0.001$) include the following. Households that include elders (x_{elder}) were less likely to reduce consumption (y_{red}). Those who lived in a single-family home, duplex, or townhome (x_{house}) were less likely to visit a relative's or friend's house (y_{visit}) or stay at a relative or friend's house (y_{rel}) than others (e.g., those living in a group home, mobile home, apartment, or condominium). Those who were more prepared (x_{prep}) and those who have been in their house longer ($x_{\text{yr},h}$) were more likely to use a power generator (y_{gen}). Of these, the only conclusion that agrees with the Los Angeles analysis is that those who were more prepared (x_{prep}) were more likely to use a power generator (y_{gen}).

Adaptation Groupings

Given the results in Fig. 1, which indicate that many people implemented or intended to implement multiple adaptations for a single outage event, we asked RQ 3: Which household adaptations tend to occur together? Which tend not to? To begin to address this question, we use a symmetric association rule metric called Lift defined as follows (Hahsler et al. 2005):

$$\text{Lift}(X \Rightarrow Y) = \text{Lift}(Y \Rightarrow X) = P(X \cap Y) / P(X)P(Y) \quad (1)$$

Lift measures how many times more often X and Y occur together than expected if they were statistically independent. In this application, X and Y are individual adaptations, and $\text{Lift}(X \Rightarrow Y)$ is used to measure the extent to which individuals indicating they did (or intend to do) X were less or more likely to indicate they did (or intend to do) Y as well (and vice versa). Tables 6 and 7 present, for the Texas (bold) and Los Angeles data sets (not bold), the lift values for all combinations of electric power adaptations and water adaptations, respectively. From a practical standpoint, the Lift statistic provides insight as to possible complementary and substitution effects among adaptations as well as information about how households optimized their adaptations portfolio.

Focusing on the Texas results (bold), Table 6 suggests a few points. First, four adaptations [charging cell phone, laptop, and/or tablet at work and/or in a coffee shop (y_{shop}); visiting a relative's or friend's house for their heat (y_{visit}); staying at a relative's or friend's house (y_{rel}); and using your car for warmth (y_{car})] tended to occur together, as indicated by those six pairs having lift values of 1.63 to 3.48. This could suggest that people substituted or switched among multiple efforts to stay warm—going to a coffee shop, relative's or friend's house, and car. The nonbold values in Table 6 suggest similar conclusions based on the Los Angeles data, although with smaller lift values.

Second, a couple of lift values suggest that people may use a single piece of equipment to support multiple uses. Charged cell phone in the car (y_{car}) and Used your car for warmth (y_{carw}), both of which make use of one's car, tended to occur together (lift = 2.39). Similarly, using your gas stove for warmth (y_{stovew}) and using a gas stove and/or camping stove to cook meals and/or boil water (y_{stove}), both of which make use of a gas stove, tended to occur together (lift = 2.36). Third, reducing and delaying consumption were twice as likely to be done by the same household as would be expected if they were independent (lift = 2.05), consistent with these being complementary actions used to form an optimal mix of adaptations.

Finally, several adaptations tended to be less common when one uses a generator (lift values of 0.48 to 0.70). These include visiting a relative's or friend's house for their heat (y_{visit}); staying at a relative's or friend's house (y_{rel}); charging cell phone, laptop, and/or tablet at work and/or in a coffee shop (y_{shop}); using a gas stove for warmth (y_{stovew}); using a car for warmth (y_{carw}); and charging cell phone in the car (y_{car}). This makes sense because a generator can support a variety of power uses, and thus other adaptations are less likely to be required. The nonbold values in Table 6 suggest a different interpretation based on the Los Angeles data because the lift values between generator and the other adaptations are all greater than one.

The lift matrix for the adaptations to water supply interruptions, presented in Table 7, offers less evidence that some adaptations tended to occur together and some did not. Across all adaptation pairs, all but one lift value was in the range 0.90 to 1.77. The results shown here do not include information about the timing of adaptations, and in particular, if a person who did two different adaptations did them concurrently or in sequence, and if the latter, in

Table 6. Matrix of lift for all electric power adaptations

Adaptation	Candles/ flashlight	Heater/ fireplace	Stove/ BBQ	Car (charge cell)	Coffee shop	Reduce consumption	Delay consumption	Visit relative	Stay relative	Stove (warmth) ^a	Car (warmth) ^a
Power generator	0.88 1.07	1.14 1.64	1.47 1.4	0.6 1.21	0.48 1.33	1.08 1.24	1.07 1.21	0.53 1.48	0.7 1.52	0.64 —	0.19 —
Candles/flashlight	—	1.28 1.13	1.28 1.14	1.31 1.11	1.24 1.09	1.32 1.1	1.32 1.11	1.22 1.05	1.33 1	1.3 —	1.31 —
Heater/fireplace	—	—	1.57 1.47	1.28 1.26	1.49 1.38	1.54 1.28	1.39 1.28	1.64 1.48	1.14 1.49	0.85 —	1.33 —
Stove/BBQ	—	—	—	1.42 1.28	0.22 1.3	1.4 1.27	1.32 1.25	0.98 1.31	0.75 1.26	2.36 —	1.55 —
Car (charge cell)	—	—	—	—	2.09 1.28	1.25 1.24	1.97 1.22	1.57 1.24	1.74 1.21	1.59 —	2.39 —
Coffee shop	—	—	—	—	—	0.97 1.28	0.94 1.24	2.78 1.43	3.48 1.39	1.44 —	3.09 —
Reduce consumption	—	—	—	—	—	—	2.05 1.33	1.61 1.36	1.34 2.11	1.08 —	1.33 —
Delay consumption	—	—	—	—	—	—	—	1.33 1.23	1.1 1.19	0.98 —	1.2 —
Visit relative	—	—	—	—	—	—	—	—	3.46 1.96	0.53 —	2.48 —
Stay relative	—	—	—	—	—	—	—	—	—	0.93 —	1.63 —
Stove (warmth)	—	—	—	—	—	—	—	—	—	—	1.87 —

Note: Bold = Texas; and not bold = Los Angeles.

^aNot included in Los Angeles data.**Table 7.** Matrix of lift for all water adaptations

Adaptation	Bottled water	Reduce consumption	Delay consumption	Stay relative	Visit relative	Melt snow ^a	Provided by community ^a
Stored water	0.97 1.09	1.3 1.21	1.37 1.28	0.95 1.38	0.97 1.34	1.05 —	1.1 —
Bottled water	—	0.94 1.14	1.01 1.11	0.97 1.11	1.24 1.14	1.04 —	1.02 —
Reduce consumption	—	—	1.43 1.27	0.98 1.11	1.07 1.17	1.05 —	0.88 —
Delay consumption	—	—	—	0.93 1.11	1.09 1.1	1.11 —	0.9 —
Stay relative	—	—	—	—	1.77 1.62	1.23 —	1.38 —
Visit relative	—	—	—	—	—	1.72 —	2.11 —
Melt snow	—	—	—	—	—	—	1.28 —

Note: Bold = Texas; and not bold = Los Angeles.

^aNot included in Los Angeles data.

what order. Better understanding the timing of multiple adaptations is an area for future research. Generally speaking, these findings suggest that water outages may be fundamentally different than power outages and thus require potentially different or unique policy recommendations.

Unhappiness

The last three research questions relate to the impacts of service interruptions on households, specifically in terms of the unhappiness experienced as a result of them. RQ 4 asks “How unhappy are households when service is interrupted?” In the Texas survey data,

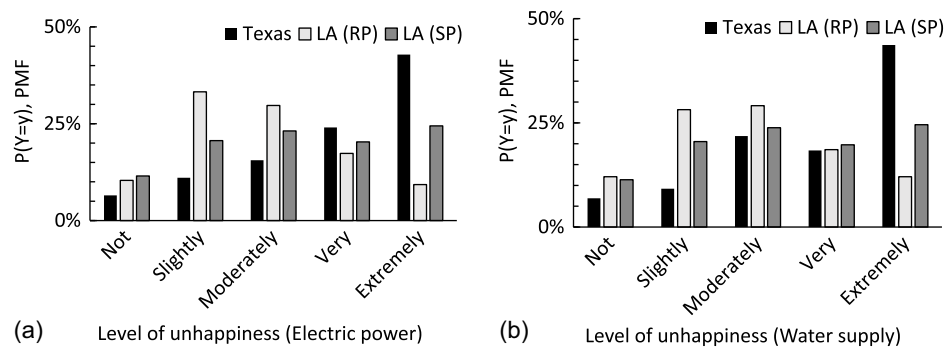


Fig. 3. Empirical probability mass function for Unhappiness by data set for (a) electric power; and (b) water supply.

when asked “Considering the actions you took to deal with the electricity [water] disruption that you experienced, as well as any remaining reduction in service, what level of unhappiness did you feel as a result of the outage?” (Q6 in the “Data Summary” section), the most common response was the highest level of unhappiness, Extremely unhappy, for both electric power (43%) and water (44%) outages, as shown in Fig. 3. Only 6% and 7% of respondents were Not unhappy due to electric power and water supply interruptions, respectively. The distribution across unhappiness levels was quite similar for electric power and water.

By comparison, respondents in the Los Angeles survey reported lower levels of unhappiness in both revealed preference and stated preference questions. The lower levels of unhappiness in the Los Angeles RP questions may be explained by the fact that the outage durations reported were shorter in general than those experienced by respondents in Texas (“Comparison with Los Angeles County Data” section). In Texas, the average outage durations for electric power and water were 62 and 101 h, respectively, versus 19 and 25 h for Los Angeles RP questions.

Interestingly, however, even though the Los Angeles SP data had higher outage durations on average (240 and 240 h for electric power and water), the unhappiness reported in those were also lower than the Texas data (although higher than the LA RP data). Although this finding merits additional study, it could be that an actual recent outage experienced with its associated discomfort (Texas) elicits more emotion and thus reports of unhappiness than

a hypothetical future outage (LA SP). The finding may suggest that people underestimate the adverse impacts of future events, particularly those with low probability of occurrence.

Predictors of Household Unhappiness Related to Service Interruptions

We used regression analysis to examine the relationship between unhappiness and the possible explanatory variables. However, as the sample size is limited, we restricted the set of explanatory variables to those considered of most interest and those that Stock et al. (2023) found to have a relationship with unhappiness (listed in Table 8). The variable Did at least one travel-based adaptation (x_{adapt}) with choices 0 = No and 1 = Yes was included to examine if/how implementing adaptations that require travel related to people’s unhappiness. The Texas sample included 105 No values and 59 Yes values. The following adaptations were classified as requiring travel: Charged cell-phone, laptop, and/or tablet at work and/or in a coffee shop (y_{shop}), Used Wi-Fi somewhere other than home (y_{wifi}), Went to a warming center (y_{center}), Visited a relative’s or friend’s house (y_{visit}), Stayed at a relative’s or friend’s house (y_{rel}), Moved to a hotel (y_{hotel}), and Traveled out of town (y_{town}).

Unhappiness, z , was measured on an ordinal scale, meaning the order of the levels is important, but the difference between levels is not necessarily constant. In addition, for respondents who experienced both an electric power outage and a water supply outage,

Table 8. Unhappiness model for Texas with corresponding values for LA

Explanatory variable	Texas		Los Angeles	
	Estimate (β)	<i>p</i> -value	Estimate (β)	<i>p</i> -value
Type, x_{type}	0.14	0.701	−0.11	<0.001
Number of interruptions (>once), $x_{e,num}$	1.61	<0.001	—	—
Prior notice, x_{notice}	−0.34	0.497	—	—
Work, $x_{e,work}$	−0.14	0.773	0.44	0.003
Worry, $x_{w,emer}$	2.26	<0.001	0.69	<0.001
Elders, x_{elder}	−0.62	0.188	−0.28	0.013
Med condition, $x_{med,c}$	−1.13	0.042	0.42	<0.001
Marital, $x_{marital}$	−0.37	0.442	0.20	0.037
Outage duration, x_{dur}	0.003	0.448	0.35	<0.001
Preparation, x_{prep}	−0.004	0.961	−0.02	0.088
Income (thousands of USD), x_{inco}	0.002	0.655	0.002	0.006
Adapt (travel-based), x_{adapt}	2.10	<0.001	0.092	0.024
Threshold1	−2.28	0.017	−3.18	<0.001
Threshold2	−0.40	0.337	−0.98	0.051
Threshold3	1.56	0.052	1.02	0.021
Threshold4	3.43	<0.001	3.59	<0.001

Note: Bold indicates variables that are statistically significant at $\alpha = 0.05$.

Table 9. Confusion matrix for the Texas unhappiness model

Observed	Predicted				
	Not unhappy	Slightly unhappy	Moderately unhappy	Very unhappy	Extremely unhappy
Not unhappy	0	1	9	5	1
Slightly unhappy	0	6	14	3	2
Moderately unhappy	0	3	19	15	6
Very unhappy	0	2	8	14	29
Extremely unhappy	0	2	9	23	70

there are two observations, one associated with each infrastructure system type (i.e., choice occasion). Thus, we use an ordered logit model with random effects to represent the relationship between unhappiness and the explanatory variables. Specifically, the ordinal response Z_{it} takes on a value of k when individual i in choice occasion t falls into the k th ordered category, where $k = 1, \dots, K$. The probability that individual i in choice occasion t is in category k is p_{itk} , and the cumulative probability is $P(Z_{it} \leq k) = \sum_{l=1}^k p_{itl}/p_{itl}$. The function that links the probability to the linear predictor is the logit link [Eq. (2)] and the cumulative probability is as in Eq. (3):

$$\log\left(\frac{P(Z_{it} \leq k)}{1 - P(Z_{it} \leq k)}\right) = \alpha_k - (\vec{x}_{it}^T \vec{\beta} + \theta_i) \tag{2}$$

$$P(Z_{it} \leq k) = \frac{\exp(\alpha_k - (\vec{x}_{it}^T \vec{\beta} + \theta_i))}{1 + \exp(\alpha_k - (\vec{x}_{it}^T \vec{\beta} + \theta_i))} \tag{3}$$

where the thresholds separating the k categories are $-\infty = \alpha_0 < \alpha_1 < \dots < \alpha_{K-1} < \alpha_K = +\infty$; $\vec{x}_{it}$ is the covariate vector; $\vec{\beta}$ is the vector of regression parameters; and the unknown random subject effect θ_i represents the influence of individual i on their repeated assessments. The models were fitted in R (R Core Team 2022) using the mixor package (Archer et al. 2015; Hedeker and Gibbons 1996).

Table 8 summarizes the unhappiness model fitted using the Texas data, as well as a similar model based on the Los Angeles data. Two variables were not included in the Los Angeles data: number of interruptions and prior notice. However, we added travel-based adaptation to LA survey data and ran the model to reveal its effect. The confusion matrix, given in Table 9, suggests that the model provides a reasonable fit to the data, predicting the unhappiness level correctly for 45% of respondents and within one level for 83% of respondents. The McFadden’s R^2 values for the Texas and LA models are 0.145 and 0.207, respectively.

The Texas results suggest that respondents are more unhappy if they experience more than one outage (versus one) (x_{num}), worry more about an emergency in the next 5 years ($x_{w,emer}$), did a travel-based adaptation (x_{adapt}), and/or do not include someone with a medical condition in the household ($x_{med,c}$). Of these, only the conclusion about worry agrees with the Los Angeles results. The finding that having someone with a medical condition in the household is associated with less unhappiness conflicts with the results of the Los Angeles model and intuition.

Although we cannot provide a definitive reason for the contradiction, it may lie in the respondent’s interpretation of a medical condition. The absence of evidence for some variables in the Texas model may be due to low power from a small size and does not imply that they do not have an effect or are unimportant. For instance, although the estimated coefficient on outage duration has the hypothesized sign, it is not statistically significant in the Texas model. Even when number of interruptions (x_{num}) and prior notice (x_{notice}) are removed, outage duration is not statistically significant

($p = 0.13$) in the Texas model. One possible explanation is the limited variability of outage duration in the Texas data versus the Los Angeles data, indicated in Table 3.

Concerns Influencing Level of Unhappiness

The final research question asks “What are the concerns that influence an individual’s level of unhappiness associated with service interruptions?” Specifically, respondents were asked to identify the extent to which each of four concerns influenced their assessment of their level of unhappiness—financial, time/effort, health, and stress (Q7 in the “Data Summary” section). In Texas, as in Los Angeles, for both electric power and water, all four concerns influenced the level of unhappiness. In fact, Fig. 4 shows the extent to which each of the four concerns played a role were quite similar in Texas and Los Angeles.

Considering both electric power and water, in Texas, 33%, 71%, 61%, and 80% financial, time/effort, health, and stress concerns were considered to at least a moderate extent, respectively. In Los Angeles, the analogous values were 37%, 59%, 45%, and 63%. Notably, stress and time/effort were especially influential in Texas. Given these concerns are found to be important across samples and for both outage types, similar or identical policies addressing household concerns may be more efficient as opposed to unique or individualized policies.

Conclusions and Future Work

This paper adds to the nascent literature on household adaptations to and impacts from infrastructure system service outages. The analysis of the 2021 Texas winter storm provides additional evidence for a few findings previously reported in the Los Angeles study (Abbou et al. 2022; Stock et al. 2023). First, both studies suggest that adaptations are quite common (RQ1). Almost everyone implements at least one; most implement several. Further, the most common adaptations tend to be relatively inexpensive (e.g., candles, flashlight, and/or lantern; charging the cell phone in the car; bottled water; and delaying or reducing consumption); the least common involve travel (e.g., going to a hotel or friend’s or relative’s house).

Second, both studies indicated that households experience varied levels of unhappiness, and they tend to be similar for electric power and water supply interruptions (RQ4). The reported levels of unhappiness were notably higher in the Texas data than the Los Angeles data, however, which could be due to a combination of outage durations (which were shorter for the RP Los Angeles data) and actual recent experience versus expected experience (from the SP Los Angeles data). Third, financial, time/effort, health, and stress concerns all had a substantial influence on the extent of unhappiness, and the Texas and Los Angeles analyses suggested they do to similar degrees (RQ6). This suggests that it is critical to consider these harder-to-measure concerns in addition to financial effects of service interruptions.

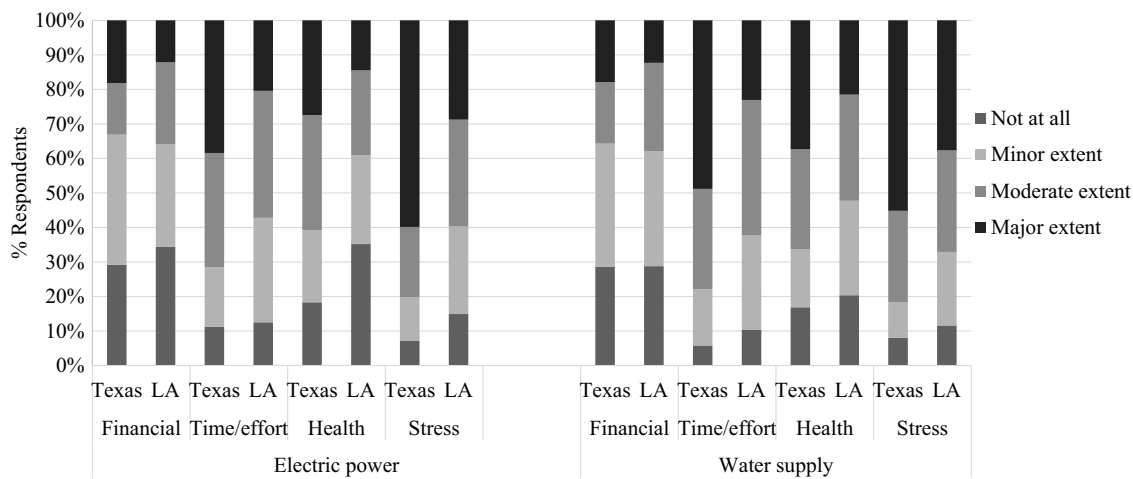


Fig. 4. Extent to which concerns are considered in evaluating unhappiness.

The results related to the predictors of adaptation implementation, unhappiness, and adaptation groupings (RQ2, RQ3, and RQ5), were more mixed. In general, the Texas data provided less evidence of relationships between specified explanatory variables and either adaptations or unhappiness perhaps due to the smaller sample size. In some cases, the data offered evidence that support the Los Angeles study (e.g., a longer outage duration is associated with increased likelihood of staying with a relative or friend). In a few cases, it offers contradictory evidence (e.g., having someone in the household with a medical condition is associated with increased unhappiness in Los Angeles, but decreased unhappiness in Texas). The Texas study also introduced the new finding that the number of interruptions can be important in determining both adaptation implementation and unhappiness.

This research includes limitations and opportunities for future extension and improvement. Most importantly, the sample of data from the Texas event was relatively small and more White, female, and educated than the population from which it came. Collecting more data from additional events in different locations would be extremely helpful in further clarifying household experiences in service outages. In general, the survey instrument used in the two deployments discussed here proved to be valuable in addressing the research questions posed and using consistent questions for multiple events facilitates an understanding of generalizability of findings.

Nevertheless, this study does suggest a few modifications to the survey instrument. First, some of the adaptation definitions might be refined so that they do not overlap (i.e., each action is represented by exactly one adaptation, unlike travel out of town and move to hotel, for example). Together, they represent a relatively complete set of adaptations implemented in most electric power and water supply outages; and they are defined based on use (e.g., warmth, cooking, and charging) and/or method (e.g., using car, stove, or going to coffee shop) in a consistent way. Second, given the importance of stress and time/effort in determining unhappiness, future work should explore what causes those concerns and how they manifest. Finally, it will be valuable to understand more about why people do or do not implement adaptations under different circumstances—due to lack of financial or other resources, lack of desire for the service, or some other reasons.

Data Availability Statement

All survey data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

The authors thank the National Science Foundation for financial support of this research under Award CMMI-1735483.

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