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Searching for signal and borrowing wi-fi: Understanding disaster-related adaptations to telecommunications disruptions through social media

Hannah Van Wyk [a,*,1], Osiris Cruz-Antonio [a], Diana Quintero-Perez [a], Sayra Damian Garcia [a], Rachel Davidson [b], James Kendra [b], Kate Starbird [a]

[a] University of Washington, 3960 Benton Lane NE, Seattle, WA 98195, USA
[b] University of Delaware, Newark, DE 19716, USA

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ABSTRACT

Disaster events can expose the vulnerability of telecommunications infrastructure to service disruptions. During these traumatic events, when connectivity is most needed, it sometimes takes days, or even weeks or months, for normal service to return. Affected people and communities attempt to adapt to these disruptions in creative ways, but this can lead to changing demands on other parts of the infrastructure. To understand the societal impacts of disasters and inform disaster preparation and response, it can be valuable to understand these behavior changes. In this research, we look to social media (Twitter) to provide insight into how people in Puerto Rico adapted to extended telecommunications disruptions after Hurricane Maria in September 2017. First, to address the challenge of limited signal within the noise of online discourse, we articulate an approach for using machine learning to detect adaptations to telecommunication disruptions in a massive Twitter dataset. Next, using a grounded approach, we developed and applied a qualitative coding scheme that revealed the different ways that people adapted to disruptions in cell service, Wi-Fi access, and electricity for their communication devices. Some of these adaptations demonstrate affected people's willingness to go to great lengths to access telecommunication services, and shifts in how people relied in new ways upon existing infrastructure — e.g. as schools become a place to charge devices. These findings offer empirical insights about how people adapt to telecommunications disruptions as well as methodological contributions around using social media as a signal for informing disaster research and response.

1. Introduction

In September 2017, two major hurricanes (Irma and Maria) struck Puerto Rico in rapid succession. Afterwards, millions of Puerto Ricans were left without power, most for extended periods of time. Three months after the storm, approximately 50% of Puerto Ricans still lacked electricity [1], and some residents were still experiencing outages more than ten months after the initial impacts [2]. This sustained disruption to the electrical grid impacted the lives of Puerto Ricans in myriad ways, including severely limiting their ability to communicate with each other and with the outside world. Across the globe, people increasingly rely on telecommunications

* Corresponding author. Address: M5326 SPH II 1415 Washington Heights Ann Arbor, MI 48109.
E-mail addresses: hcvw@umich.edu (H. Van Wyk), rdavidso@udel.edu (R. Davidson), kstarbi@uw.edu (K. Starbird).
1 Current address: M5326 SPH II 1415 Washington Heights Ann Arbor, MI 48109.

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infrastructure dependent upon the electrical grid—from cell phones to social media to online websites—to communicate and access information. Unfortunately, as the case of Hurricane Maria demonstrates, this infrastructure is acutely vulnerable to disruption from disaster events, arguably during times when people need information the most. In this research, we turn to the social media record to explore how people adapt to long-term disruptions to telecommunications infrastructure during this era of otherwise ubiquitous connection.

Social media are reconfiguring how humans communicate, including how we communicate during disaster events. Research shows people turning to social media during disasters to gather information, inform others, and participate in collective sensemaking activities (e.g., Refs. [3–6,7]. Because social media activity produces and leaves behind a digital record, these sites can become resources for research [5,8]. Much of this research has focused on using social media as a signal for impacts, often to inform solutions for rapidly identifying and communicating information to responders that could contribute to situational awareness (e.g., Refs. [9,10,11]; [6,12,13]. More recent lines of inquiry center actionable information that responders and affected citizens could use for decision-making [14] and specifically, information about disruptions to critical infrastructure [15,16]. In this study, we shift the focus to social media as a signal for *adaptations*, i.e., how people respond to and work around disaster-induced disruptions to physical infrastructure.

Adaptations to sudden shifts in the environment have been noted as primary features of individual, group, and societal resilience [17]. noted that the quality of *bricolage*—making use of what is at hand, recombining resources and knowledge into new forms—supported resilient responses by organizations under stress [18]. apply this concept to studying individual and collective responses to disaster events, describing how people adapt to disaster-related disruptions by translating the social and technical affordances in their environments into "creative and innovative actions" to meet existing and emergent needs.

Several benefits can arise from a greater understanding of how people adapt to infrastructure failures. Before a disaster, crisis responders and service providers can prepare to help people adapt temporarily. Understanding people's adaptation needs and habits can also help responders prepare for the spinoff effects, such as, people in search of gasoline, traveling to find cell service or a place to charge their phones, and visiting public buildings or hospitals in search of electricity or Wi-Fi. During an event, knowing how, where, and when people are likely to implement these adaptations can help responders channel resources accordingly.

Previous research has explored how people adapt to disaster events generally (e.g. Refs. [19,20], and to disruptions in telecommunication infrastructure more specifically (e.g., Abi [21,22]. However, those studies have relied primarily on after-the-fact interviews and surveys. Our work turns to the social media record, examining adaptations through the contemporaneous posts of people who were enacting (and talking about) them.

Here, we present a mixed-method analysis of Twitter data that reveals how people adapted to long-term telecommunications disruption from Hurricanes Irma and Maria. Irma and Maria, which caused both acute and prolonged impacts to the electrical grid and, consequently, disruptions to telecommunications services on the island. Contemporaneous media coverage described how affected people on the island were adapting to these disruptions — for example by changing cellular phone providers [23] and traveling to locate better cellular service [24]. Through systematic analysis of social media trace data from people who were in Puerto Rico at the time, our research aims to identify, enumerate, and understand the different ways that Puerto Ricans adapted to sustained telecommunications disruptions due to Maria's impact on the electrical grid. We focus on adaptations of three different types: accessing cellular service, accessing Wi-Fi, and charging communication devices such as mobile phones, tablets, and laptops.

We first utilize a machine learning approach to identify adaptations in tweets, then employ qualitative analysis to identify, categorize, and understand the different kinds of telecommunications adaptations that appear in the Twitter data. The challenge in the first part is finding signal in the noise — as adaptations are only mentioned within a tiny proportion of the millions of tweets we collected. After developing a method for homing in on that signal (detecting adaptations tweets), we then map those adaptation tweets over time — revealing the contours of the extended disruptions and the work affected people did to adapt to them.

This work offers two primary contributions. The first is empirical, enhancing our understanding of how people adapt to sustained telecommunications disruptions. The second is methodological, providing insight into how we can use social media to learn — both after-the-fact and potentially in real-time — about how people adapt during disaster events to disruptions to critical infrastructure.

2. Background

2.1. Adaptations to disaster-related disruptions

The availability of built infrastructure of every type (e.g. power, water, telecommunications) is a defining feature of modernity, but increasing dependence on that infrastructure also presents one of modern society's greatest risks [25]. This vulnerability is especially acute during disaster events — such as earthquakes and hurricanes — which can damage that infrastructure and disrupt people's ability to access and use that infrastructure to meet their needs. During those disruptions, people adapt, for example by relying upon different social or physical resources, changing their routines, or reducing their consumption.

The study of adaptations in crisis has been an important element of disaster research, typically considered as improvisations or creativity. For example, after the 9/11 attacks in New York City forced the closure of all the bridges and tunnels leading into Manhattan, an impromptu boat network became a key transport adaptation. How people adapt points to elements of coping and resilience, through new tools, repurposed tools, or social systems. In the 9/11 case, boat operators and waterfront workers blended new and old tools and technologies, and new and old acquaintances, to build a new transport system [26]. Along the way, they showed that mobile and mutable artifacts could back up more established systems in a crisis.

Adaptations often take the form of using an older but more durable technology. Candles replace electric light; amateur radio replaces the internet.. In the example of the fireboat John J. Harvey in New York City on 9/11 [26], argued that retired vessel, brought back into service to pump water at Ground Zero, showed how seemingly old or obsolete technologies can suddenly be important again.

Often, though, these adaptations replace only a portion of the capability provided by the service they are replacing, necessitating other kinds of coping, often behavioral or affective. Other adaptations tap into social systems and networks. A cell phone, though seriously impaired as a communications device if there is no wireless service, can be chained to other cell phones via Wi-Fi and Bluetooth apps, or people can direct others to where service is available. These adaptations, however, come with costs of time, labor, even danger if people have to travel to precarious locations.

Interest in critical infrastructure failures is growing due to the prevalence of these failures in disasters or through system decay and degradation. As examples [20,27], studied how people coped with power failures in Scandinavia [22]. studied coping following the 2010 Chilean earthquake, while [28] examined the impacts of electric power failures after Hurricane Irma. Though Chakalian et al. broadly classified adaptations into *material*, *social*, and *intellectual* resources, there are few broad typologies or organizing frameworks or studies that build on others to develop an integrated base of knowledge. Using survey data from Los Angeles, California [29], quantitatively analyze household adaptations to electric power and water supply interruptions, in particular, who tends to implement which ones, how often, and under what circumstances. Nevertheless, knowledge about which adaptations are most likely, which are most practicable, and which are most efficacious in meeting people's needs, will be foundational to future studies of community resilience. This paper, focusing on telecommunications adaptations, advances this literature by capturing accounts of adaptations recorded in real time with the adaptation.

In particular, in this work we focus on adaptations to disruptions to telecommunications. Access to information is vital for people experiencing disaster events — to understand the impacts of the unfolding event and to make decisions about how to respond. Increasingly, affected people are relying upon cellular and internet-based technology to get the time- and safety-critical information they need during disasters (e.g., Refs. [4,30,11]. However, these communication modalities are often dependent upon the same infrastructures (i.e., the electrical grid and telecommunications network) that are impacted, rendering people acutely vulnerable to communication disruption during the times when they need information the most [30,31]. Our research focuses on this increasingly relevant dimension of disaster-related disruption.

2.2. Social media as a resource for understanding disaster impacts

This study looks to social media as a resource for understanding how people are impacted by — and how they adapt to — an extended disaster event. Social media are used by affected people to seek and share information during disaster events (e.g., Refs. [4,30,31]. Digital volunteers, including people who are not affected, also converge onto these platforms during disasters to try to help those who are [6,32]. Disaster responders turn to these platforms as well (e.g. Refs. [6,30,33], — both to share information with their communities and as an informational resource. Many of these activities leave behind digital traces, often public ones, that constitute a contemporaneous record of the disaster and human responses to it.

For more than two decades now, researchers have used digital trace data, including social media, to understand disasters [8]. The research presented here extends, in part, from foundational work in crisis informatics [5] seeking to leverage the digital record to learn about how people are affected by and respond to disasters.

A prominent dimension of crisis informatics research seeks to develop real-time solutions that make sense of social media at scale to inform disaster response. Since the rise of social media, online volunteers, journalists, and researchers have explored the potential of using social media as "signal" during crisis events — e.g., by collecting and processing social media data into informational resources for affected communities and responders [34,10]. These efforts have proven challenging, in part due to the overwhelming volume of content and the difficulty of filtering signal from noise. Responders have remarked about having to "drink from the firehose" [35].

Acknowledging these challenges, crisis informatics researchers have investigated automated solutions for rapidly processing large-scale social media data — both as a research tool and, potentially, as part of a solution for information response efforts (e.g., Refs. [15,16,36–38]. One line of research, initially introduced by Ref. [11], focuses on using natural language processing and other machine learning techniques to identify and classify content on social media that could contribute to "situational awareness" for crisis responders (Reuter, 2018; [6]. Another research trajectory seeks to identify "actionable" information that can be used by affected citizens and/or responders to make informed decisions [14,39]. More recently, researchers have developed and evaluated methods for using social sensing to detect disruptions to critical infrastructure [15,16].

While all of these approaches are valuable for understanding the different dimensions of an unfolding disaster, the vast majority of the research leveraging social media data in the disaster context focuses on uncovering information about *impacts* of the disaster — downed power lines, damaged buildings, the numbers and locations of injured and displaced people, etc. In this work, we shift the focus to what we can learn from social media about how people *adapt* to disasters.

2.3. Understanding adaptations through social media trace data

This work aims to lay the foundations for understanding adaptations to disaster events using social media signals. One benefit of this approach is that it allows researchers to learn from actual behaviors (or at least communication about those behaviors) at the time of the adaptation, rather than relying on survey instruments and interviews after the fact. It also opens up the possibility for real-time analysis — supported by computational methods including machine learning — of how people are adapting during an event, which could guide decisions about how to allocate resources.

However, there are limitations and ethical concerns to using social media in these ways. One concern is that information shared during crisis events, even when shared on public platforms, may not be intended by its authors to be used for research or to persist on public-facing resources [40]. For this reason, in this paper we attempt — through translating and adjusting the original text in our data excerpts — to make it difficult to connect the example content to their authors. Another long-standing concern has been around the tendency for researchers of social media and crisis to focus on the immediate impact phase of the disaster when the volume of social media messages about the event is high, with relatively less focus on the long-term impact on people in the affected areas [40]. Our work attempts to remedy this by using a much longer temporal window into the social media record, and by focusing on content shared by specific accounts, not just content with specific disaster-related hashtags or keyword terms.

There are concerns about representation as well. Often, the people who are the most vulnerable during a disaster event are the least likely to be able to communicate their needs (or their adaptations) through social media platforms. This can be due to disruptions from the disaster itself [41]; if someone does not have power, then they cannot connect to these platforms to share information about their situation. But it can also be due to the contours of social media use and how they reflect demographic differences across age, education, socioeconomic status, and race [8,40–42]. For example, the average age of social media users and specifically Twitter users [43] in the U.S. skews younger, with the 18–24 age group being, by far, the most active. Aligned with those trends, our data — produced by Twitter users who were likely in Puerto Rico — appear to over-represent the activities (and therefore adaptations) of young people.

Additionally, certain kinds of adaptations may be more likely to appear in social media data than others — even if people are making them at the same rate. For example, in the Hurricane Maria data, posts about telecommunications adaptations are more common than other kinds of adaptations in the social media trace data, possibly because affected people were in the process of adapting to telecommunications disruptions when they were using social media and therefore tweeted about them at higher rates. This is largely why this research focuses on adaptations to interruptions in telecommunications rather than other infrastructure types—because they were most visible in this data.

2.4. Event background

This research focuses on adaptations to Hurricanes Irma and Maria, which struck Puerto Rico in quick succession in September 2017. Irma passed slightly north of the island on September 5 as a Category 5 storm, resulting in flooding, damage to homes and buildings, and significant loss of electrical and water service [44]. Hurricane Maria came ashore two weeks later as a Category 4 storm, causing catastrophic and long-term impacts. Thousands of lives were lost [45,46]. In the immediate aftermath, there was widespread flooding and damage to homes and buildings, as well as loss of power and water services.

Disruptions to telecommunications were particularly acute and long-lasting. The electrical infrastructure, already weakened by Irma and inherently vulnerable due to age and lack of investment [47], suffered significant and sustained impacts. The entire power grid of the island was affected, leaving more than 3 million residents without power in the immediate aftermath [48]. Cellular phone services, which relied on the electrical grid to operate, were initially knocked out completely and later significantly degraded as several providers struggled to find power for their networks [49]. A large proportion of phone and internet cables were damaged and unusable as well [50]. For many, the disruptions, especially those related to electrical service, were sustained, with extended and later episodic outages continuing for more than ten months [47,49].

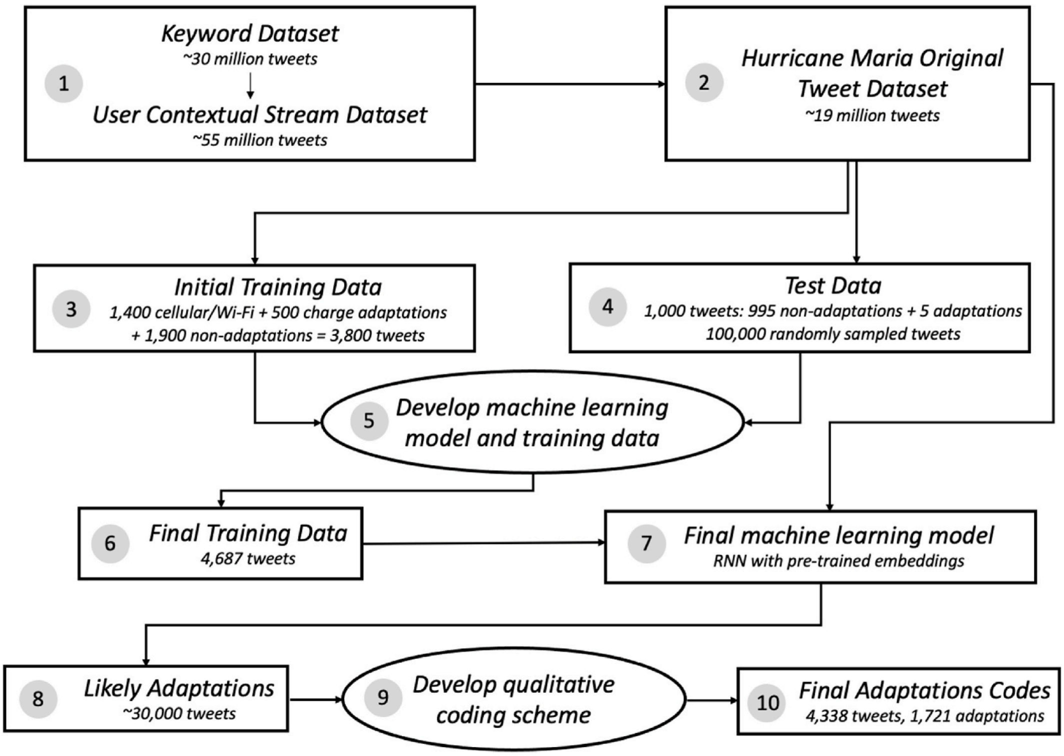

Fig. 1. Overview of datasets and methods.

2.5. Preliminary study

The research builds upon a preliminary study [51], focused on the same event and data as the work presented here, that sought to identify and describe telecommunications adaptations. In that work, we employed a heuristics-based approach to identify adaptations to the loss of cellular service and Wi-Fi, and a subsequent qualitative analysis (a lightweight clustering process) to identify different types of adaptations in the data. In particular, we highlighted how tweets indicated that people were traveling from one location to another to access both cellular service and Wi-Fi, a finding that we expand upon here.

In this paper, we build from those initial analyses, but utilize a more systematic approach to both identifying (using machine learning) and classifying (through a systematic coding process with multiple coders) adaptations tweets. We also expand the focus here to include adaptations related to charging devices. For clarity, some of the methodological steps used in the preliminary study are also described here (Appendix A), because they provided the foundations for the machine learning component of this research.

3. Methods

3.1. Overall approach

Fig. 1 summarizes the methods used and datasets developed in this analysis. The appendices provide additional details. The raw data were obtained using Twitter's Streaming API in two steps (Step 1, Fig. 1). First, we collected tweets from August 24 to November 6, 2017 with a hurricane-related keyword search (e.g., *hurricane, maria*), resulting in ~30 M tweets which we call the *Keyword Dataset*. Using this dataset, we identified accounts likely to be local to Puerto Rico (i.e., accounts with Puerto Rico in the profile description or geolocated tweets in Puerto Rico) – 43,788 accounts in total. From each "local" account, we generated a ~55 M tweet *User Contextual Stream Dataset* by capturing either the most recent 3200 tweets or all tweets from the beginning of the collection period, whichever was smaller. To capture both initial and long-term impacts, we conducted this collection four times at fairly regular intervals over the course of nine months. We eliminated retweets from these ~55 M tweets to further limit to local content, resulting in 19 M tweets used in our *Hurricane Maria Local's Original Tweets Dataset* (Step 2, Fig. 1).

Next, as a starting point for automated labeling of adaptations, we leveraged the 1900 adaptation tweets identified through a heuristic-based method in our preliminary research [51]. Briefly, these 1900 tweets were identified through iterated keyword searches, where each step consisted of updating the search terms to generate a result with a higher signal-to-noise ratio (as determined through manual coding). We combined these 1900 tweets with 1900 non-adaptation tweets randomly obtained from the *Hurricane Maria Local's Original Tweets Dataset* as initial training data (Step 3, Fig. 1), we trained a Recurrent Neural Network (RNN) [52] model with pre-trained word embeddings [53] to detect adaptations in the entire *Hurricane Maria Local's Original Tweets Dataset* (Step 5, Fig. 1). For each tweet, the model took the tweet text, the date, whether the tweet contains a link, and whether the tweet was directed at another user as an input then generated a prediction based on an assigned probability of the tweet containing a telecommunication adaptation.

To test the model, we used two test datasets (Step 4, Fig. 1). For the purpose of obtaining numeric performance metrics, the first dataset consisted of a random sample of 1000 tweets from the *Hurricane Maria Locals' Contextual Streams Dataset* consisting of 995 non-adaptations and 5 adaptations, manually coded using the same methodology as with the original training data. For model diagnostic and training data calibration purposes (i.e., diagnosing the cause of false positives or negatives and adjusting the training data) we used a larger dataset of 100,000 randomly selected tweets. Within these 100,000 tweets, we only manually coded the tweets given a $\geq$0.7 probability of being an adaptation for a more tractable sample size. To evaluate the performance of our model (Table A-1, Appendix A), we used the F1 score, the harmonic mean of precision and recall [54]. Using a supervised learning process [55], we improved our training data over four phases targeted at reducing false positives (non-adaptations classified as adaptations) and false negatives (adaptations classified as non-adaptations) (Step 5, Fig. 1). Briefly, in this process, we iteratively identified new adaptations the model found in the 100,000 tweets and added more examples of these to the training data, and analogously found keywords that were triggering false positives and added non-adaptation examples of tweets containing these keywords into the training data. The training data we ultimately used in our model, *Final Training Data,* consisted of around 4700 tweets, of which slightly less than half (~45%) were adaptations.

Upon achieving a F1 score of 0.910, with 42% of the tweets machine classified as $\geq$0.9 in the 100,000 being manually confirmed as adaptations (Table A-1, Appendix A), with our *Final Training Data* (Step 6, Fig. 1), we ran our final model (Step 7, Fig. 1) over our entire *Hurricane Maria Locals' Original Tweet Dataset* using the calibrated training data. From this dataset, 29,635 (or 0.15% of the total 19 million) were classified as 0.9 or above (i.e., having $\geq$90% probability of being an adaptation) — what we will call our *Likely Adaptations* dataset (Step 8, Fig. 1). Though there are likely interesting examples of adaptations within tweets with lower scores, to minimize noise for the qualitative coders in the next portion of our study, we focus on tweets that the model determined to be $\geq$ 0.9.

Applying an inductive approach to qualitative analysis, we developed a coding scheme for different kinds of adaptations that appeared in the 29,635 tweets from "local" accounts — those determined to be posting content from Puerto Rico during the lead up to and aftermath of Hurricane Maria (Step 9, Fig. 1). The qualitative research team consisted of four researchers, all fluent in Spanish and English. Together, we used an iterative process to develop the coding scheme, train ourselves to apply the codes, and improve inter-rater reliability. To develop the coding scheme, we started with a rough coding scheme based on our preliminary study [51], then proceeded to repeatedly code samples of tweets, regrouping after each cycle to see what was missing from the scheme or what would be removed. The final coding scheme, described in Section 3.2, includes relevance, modality, positionality, and temporality. In the latter part of the Findings (Section 4), we elaborate on several of the coding dimensions and some of the more interesting codes/adaptations.

Finally, once the qualitative coding scheme had stabilized, we proceeded to manually code a randomly selected set of 4338 tweets from the likely-adaptations sample that would be tractable for manual coding but large enough to conduct an analysis (Step 10, Fig. 1). Coding consisted of a multi-step process, integrating rounds of independent coding with rounds of arbitration, described in more detail in Appendix D. Each tweet was coded independently by two researchers who were fluent in both English and Spanish. Though the vast majority of our data was in Spanish, the *Likely Adaptations* dataset contained many tweets that contained words in English and several that were entirely in Spanish (likely because of the high frequency of cognates and usage of proper nouns that the model selected on), which we coded along with the Spanish-language ones.

First, we coded for relevance (adaptation, impact, not related, ambiguous). Where agreement was lacking, a third coder arbitrated. Tweets determined to be adaptations were then coded (by the same two researchers who initially coded relevance) for adaptation modality (Table 2), positionality, and temporality. Where the first two researchers disagreed, a third researcher would arbitrate, choosing one of the codes provided by the initial two coders. Among the first two coders, there was moderate agreement (Cohen's Kappa 0.70) for the coding of relevance and modality type (i.e., cellular service, Wi-Fi, charge) (Cohen's Kappa 0.63). Though we do not fully explore temporality and positionality in this paper, we coded for these and include their Cohen's Kappa in Appendix C and D. In total, we manually coded 4338 tweets, which was ~15% of the total 29,635 identified as $\geq$0.9 by our machine learning algorithm. Of these, 1721 (40%) were adaptations, 1819 (42%) were impacts, 769 (18%) were not related, and 30 (0.7%) were ambiguous.

3.2. Adaptations coding scheme

3.2.1. Relevance

The relevance category consisted of four codes: adaptation, impact, not related, or ambiguous. Not related included any tweet that was not related to a disaster impact or adaptation. The ambiguous category included tweets that had mixed signals about whether they were an adaptation, an impact, or not related. (see Table 1).

3.2.2. Modality

Telecommunications adaptations occurred across three different modalities (Table 2): cellular service, Wi-Fi, and electrical charge. Some tweets also fit into several categories and are therefore double counted as having more than one adaptation across more than one modality. Within each modality, there are different types of adaptations (e.g., going to another location, changing service provider). We describe those in detail below in sections 3.2.3 through 3.2.4.

3.2.3. Positionality

Twitter users communicated about adaptations from different perspectives — e.g., talking about how they were adapting themselves, talking about how they were helping others adapt, or talking about how others were adapting. We conceptualized this as *positionality*, and identified eight salient perspectives (listed and defined in Appendix B). Positionality can be important for understanding who is adapting (and who is providing resources for adaptations). Though (for reasons of space) we do not report directly on positionality in this paper, we do integrate some reflections on positionality in relation to certain adaptations described in the Findings (Section 4).

3.2.4. Temporality

A final category was temporality, capturing when a specific adaptation occurred in relation to a tweet. Temporality is important for understanding when different adaptations are happening, relative to the tweets mentioning them. This dimension has six different codes (listed and defined in Appendix C) — including *in progress, in progress/habitual, future/hypothetical, past, preparatory, and multiple/unclear*. Similar to positionality, we do not report specifically on temporality in this paper, but do note how it intersects with some of our adaptations.

3.2.5. Findings

In this section, we first examine the temporal patterns of the 1721 adaptation tweets, then we unpack the salient adaptations in our analysis, including several that had not surfaced in our preliminary research [51]. In particular, we describe the different adaptations that surfaced in relation to each of the three telecommunication modalities—cellular service, Wi-Fi, and charge—in turn, then, discuss other technology-based solutions and adaptations which fit into multiple of these modalities.

3.3. Timing of telecommunications adaptations

Fig. 2 shows the 29,635 tweets classified as $\geq$ 0.9 in blue and the 1721 coded adaptations in green, both plotted as relative

Table 1
Codes, definitions, and examples for the relevance dimension.

Options	Definition	Example
Adaptation	Related to a crisis event/power outage/loss of telecommunications, and contains an adaptation	"I do not like having to go to Colobos to have good service …."
Impact	Related to impacts of a crisis event/power outage but does not contain a telecommunications adaptation	"The internet came back in my apartment < raising hands in celebration emoji>"
Not Related	Not about the disaster or impacts caused by it	"I bought some stuff online and I want them to come already: ("
Ambiguous	Contains mixed signals about whether it is an adaptation, impact, or not related.	"@reply We fight over the plug to charge the cell phone < laughing emoji> "

Table 2
Examples for each modality type.

Modality Type	Example
Cellular	"There are those who have service and there are those who have to go through the whole house looking for service, I am part of the group that has to go through the whole house" [2017-10-11]
Wi-Fi	"Stealing Wi-Fi from Sears)" [2017-11-22]
Charge	"I'm going to Walmart to grab A/C and charge the cell" [2018-03-01]

percentages of the total. The temporal graph of likely adaptations (blue) has two spikes — one for Hurricane Irma on September 5, 2017, and the second immediately before Hurricane Maria on September 20, 2017. The dip immediately following Maria striking the island is likely due to impacts of the disaster making it difficult for affected people to tweet. The graph rises again through early October as people begin to be able to use their phones to tweet about how they are adapting, with a gradual decline after that, extending through early 2018. The spike on April 18, 2018 results from an island-wide power outage that happened on that day [56].

The temporal pattern of the coded adaptations (green) is similar, which suggests that the noise in the *Likely Adaptations* dataset is relatively equally distributed across the time window. However, there is a noticeable trend of greater proportions of the confirmed adaptations occurring on the date of Hurricane Irma and in the aftermath of Hurricane Maria — which may indicate that tweets from those time periods were more likely to be adaptations.

Fig. 3b plots the relative frequencies of adaptations across the different modalities: Wi-Fi, Cellular, and Charge. All spiked during the few days following Hurricane Irma, however the trend is different after Maria. The cellular adaptations rise and peak earliest, then the Wi-Fi adaptations which feature a long plateau, followed by the charge adaptations which rise later and never reach the same overall volume as the other two types. The charge adaptations have a local peak right before Hurricane Maria made landfall — revealing that people were tweeting about how they were charging their devices in preparation for the impending disaster (Tweet 1).

> Tweet 1: "Constantly charging my phone in case my power goes out." [2017-09-20]

Interestingly, tweets about charging devices are at a very low volume immediately following the hurricane impact, and only begin to rise about a week later, perhaps as people started to identify strategies for accessing electricity.

For comparison, we also include a plot (Fig. 3a) of the percentage of Puerto Rican energy customers who were without power over the same time period. Notably, the temporal graph of tweeted adaptations (Fig. 3b) aligns well with the temporal graph of actual power outages (Fig. 3a) — except for the initial few weeks after the event, when the social media signal for adaptations was likely dampened due to affected people being unable to adapt (or to tweet about adapting) to telecommunications disruptions.

3.4. Cellular adaptations

We coded 708 tweets as adaptations to cellular service. Within this, there were 11 categories of adaptations, including several subcategories within the changing location category (Fig. 4).

3.4.1. Changing location

We classified any tweets that mention going to a place that has cellular service as "changing location" which accounts for 367 (52%) of the 708 cellular-related adaptations, making it the most common cellular adaptation. Because many tweeters imply their change of location without explicitly stating it, we included tweets with both explicit and implicit mentions of changing location.

One popular trend was tweeting about good cellular service (when a person managed to find it). This implied an adaptation by the tweeter (positionality: adapting myself or adapting ourselves) to the common shared experience of unreliable cellular service throughout the island. Those tweets also served to provide information to others (positionality: information sharing) about locations with reliable cellular service. These were especially useful if the specific cellular network provider was mentioned, as seen in Tweet 2:

> Tweet 2: "The panadería Apolo is also open. There is T-Mobile service in Altamira. The spots are very full. Anyways, keep reporting." [2017-09-26]

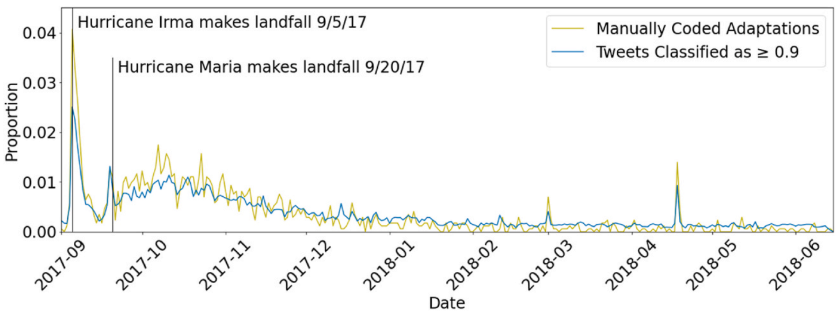

Fig. 2. Proportion of tweets per day of the coded adaptations (green) and the total tweets that were classified as ≥ 0.9 (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

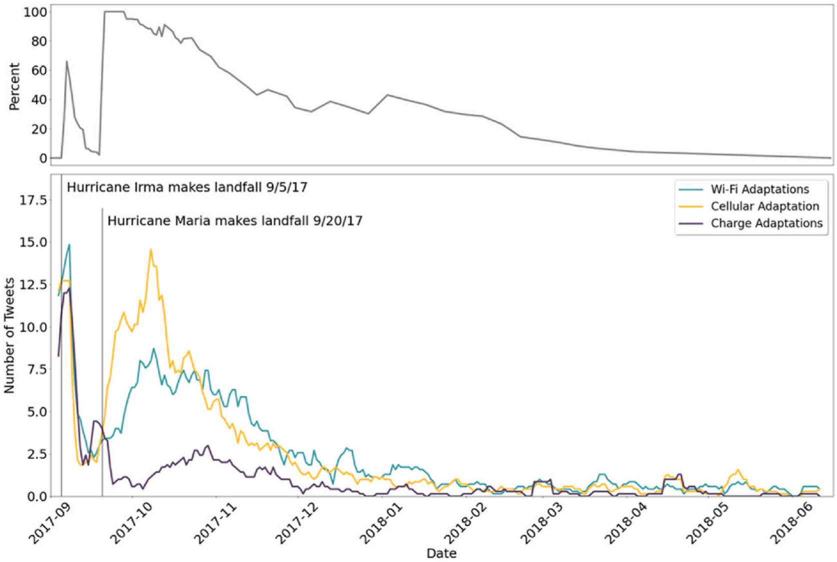

Fig. 3. (a) Percent of electric customers in Puerto Rico without power [57,58] (b) 7-day rolling averages of the number of adaptation tweets per modality per day.

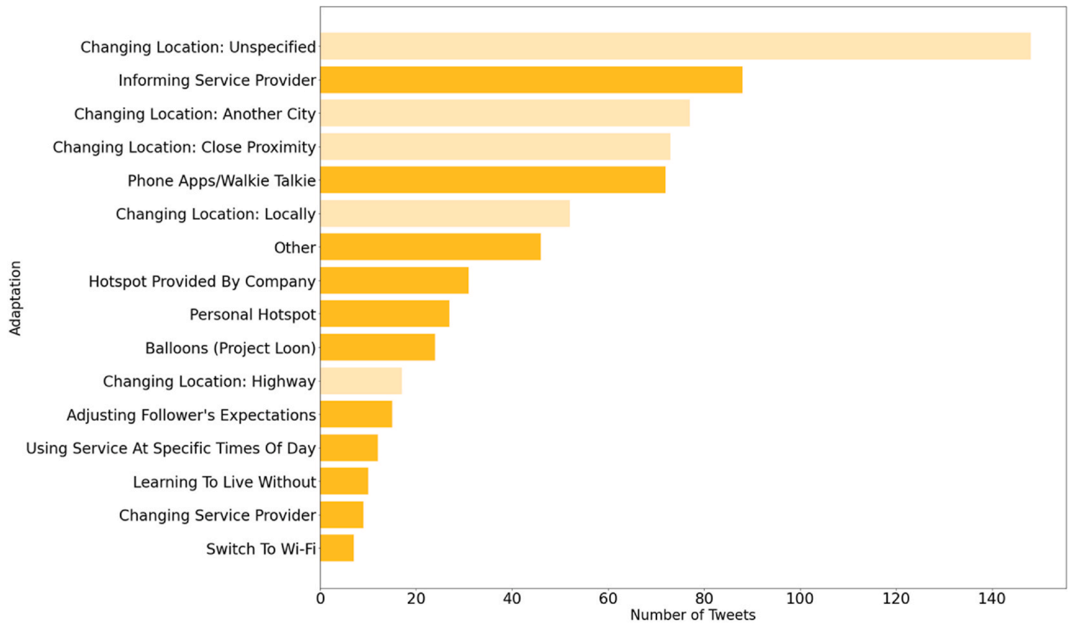

Fig. 4. Number of tweets that are cellular adaptations, by adaptation category.

To better understand *where* adaptations were occurring and how far individuals were traveling to adapt to cellular service disruptions, we added several location-specific sub-codes to our scheme: close proximity, locally, another city, and highways.

3.4.1.1. Changing location: close proximity. This code captures any tweets that mention changing location anywhere around the current building (usually the home) of the tweeter including: going onto the roof, balcony, another room, the yard, or the street outside the building. About 10% of cellular adaptations were people moving around their homes and/or neighborhoods to access better service. One particularly interesting trend within this category is the level of discomfort and/or difficulty the adapters endured in order to get cellular connection, including braving cold weather and climbing onto the roof of their building (Tweets 3 and 4):

Tweet 3: “Dying of hypothermia on the balcony of my house, but I have fast internet.:‘)” [2017-10-01]

Tweet 4: “I found a spot with signal in the roof and I’m not moving from here” [2017-09-25]

These tweets show that although the distance the adapter traveled may not have been very large, in many cases people were putting themselves in uncomfortable — and possibly dangerous — situations to adapt to spotty cellular service.

3.4.1.2. Changing location: locally. We applied this code to tweets that either mentioned the adapter traveling within their town or city, or going to a specific business to get cellular service. Like the "close proximity" category, the relatively short travel time for finding cellular service locally does not imply that the adapter was able to find cellular service quickly, as seen in Tweet 5 which implies the tweeter traveled locally, but not that they were able to find service easily:

> Tweet 5: "Finding signal in my town is a mission" [2017-11-04]

This code notably captures the diverse array of businesses that adapters spent time within to access cellular service. These were not always businesses like cafes meant for lingering, but included drug stores and fast food restaurants, like in Tweet 6:

> Tweet 6: "I am hanging out in Walgreens because it is the only place where I have service" [2017-10-04]

This example suggests that because cellular service (unlike Wi-Fi) is not confined to a specific building, that adapters had to both find places with cellular service and make decisions on where they felt comfortable "hanging out".

3.4.1.3. Changing location: another city. More than 10% of cellular adaptation tweets indicated that the author had traveled to another city to access cellular service. We included tweets that mentioned a specific city name, because we assume that the tweeter would not mention traveling to their own city. In some cases, the tweet would clearly note the cities they traveled to and from for cellular service as in Tweet 7:

> Tweet 7: "I come to Ceiba to for T-Mobile's signal because there's nothing in Fajardo." [2017-11-03]

Unsurprisingly, this category demonstrates the amount of effort and time that went into obtaining a strong cellular signal. Not only for the travel time, but also for the traffic jams people commonly encountered, and because of the long-term service outages that caused people to have to travel frequently over an extended period of time. This is seen in Tweet 8 where the user traveled to another city nearly 20 days after Hurricane Maria and mentioned that they do this frequently:

> Tweet 8: "The only place I can get a signal is in San Patricio and I'm already tired of coming here twice a week because of the traffic." [2017-10-09]

This tweet also shows how some adaptations became part of a routine, continuing for months after the disaster.

3.4.1.4. Changing location: highway. A significant number of tweets (17) indicated that people were traveling to locations along the highway to access cellular service. We assigned this type of tweet a distinct code because it appeared to be a common behavior with potentially serious consequences. For example:

> Tweet 9: "I still wonder how so many people can have signal all the time and I have to be on the highway to get signal. <sarcastic smiley face emoji>" [2017-10-08]

The tweet implies that the adapter habitually goes to the highway to get cellular service. Other tweets provide evidence that this behavior was both sustained and widespread. For example, Tweet 10, which describes a large number of people adapting in this way,

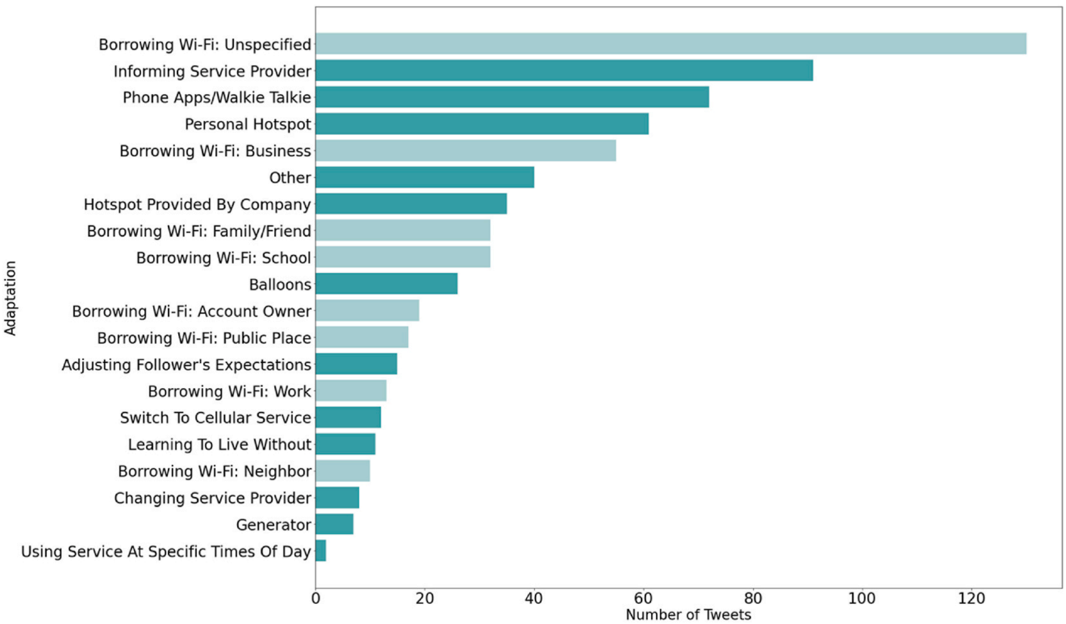

Fig. 5. Number of tweets that are Wi-Fi adaptations, by adaptation category.

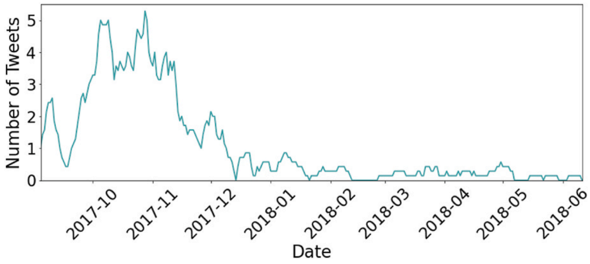

Fig. 6. 7-day Rolling Average of tweets per day of Borrowing Wi-Fi Adaptations.

was posted on November 11, 2017, more than 50 days after Hurricane Maria struck the island.

Tweet 10: "On Highway 52 <Puerto Rican flag emoji> in the road, you only see cars parked searching for cellular service or flat tires <car emoji>" [2017-11-11].

3.4.2. Using service at specific times of day

A few adapters astutely observed that their cellular service worked better at certain times of the day (or night). For some, the difference in connectivity was significant enough to prompt them to change their schedule:

> Tweet 11: "Having to get up at 12:40am to have good LTE signal #TheRealCrisisPostMaria" [2017-11-03]

Compounding impacts also forced some to make decisions about how to shape their sleep schedules to maximize access to electricity and telecommunications:

> Tweet 12: "I don't know whether to sleep to take advantage of the generator or to stay awake to take advantage of the cell phone service." [2017-10-22]

Both of these examples imply that the tweeter did not enjoy reliable access to cellular service and the dates on the tweets suggest that their normal sleep schedule may have been impacted repeatedly and over an extended period of time by the search for cellular service.

3.5. Wi-fi adaptations

There are 688 Wi-Fi adaptations, fitting into 12 codes, with borrowing Wi-Fi code having several subcodes (Fig. 5).

3.5.1. Borrowing wi-fi

Similar to "changing location" within the cellular adaptations (Section 4.2), "borrowing Wi-Fi" was our largest adaptation category for Wi-Fi, accounting for 308 (48%) of our 688 Wi-Fi-related adaptations. This adaptation consists of the adapter using a Wi-Fi network provided by another individual, organization, or place. Fig. 6 which plots the seven-day rolling average of the number of borrowing Wi-Fi tweets per day, shows Wi-Fi adaptations peaking during the month of October, then declining through the beginning of 2018.

We created seven subcodes to describe where the adapter went to borrow Wi-Fi: business, family/friends, school, public place, account owner, neighbor and work. However, as seen in Fig. 5, the majority of the tweets were coded as "unspecified" because they did not mention where they got their internet connection from, for example:

> Tweet 13: "Stealing Wi-Fi wherever I can" [2017-09-26]

Interestingly, many tweeters used the phrase "stealing Wi-Fi", suggesting that they did not feel that they were authorized to use Wi-Fi from that person or organization, but were doing it anyway.

3.5.1.1. Borrowing wi-fi: business. Borrowing Wi-Fi from a business was the most popular subcode within borrowing Wi-Fi. Businesses where people went to access Wi-Fi included restaurants, grocery stores, supermarkets, local businesses, etc., for example:

> Tweet 14: "@anonymized HAHAHAHA I finally saw this just now, I'm in Kmart borrowing Wi-Fi" [2017-10-08]

Some tweets also explicitly included information about where free Wi-Fi was available, perhaps to help others in the area experiencing similar disruptions:

> Tweet 15: "In Office Depot there is free Wi-Fi" [2017-11-10]

This example tweet and the relative frequency of the "business" subcode suggests the utility of businesses offering free Wi-Fi (even businesses where people do not usually go to browse such as grocery stores) and making this information widely available to the public. The second tweet also reveals the importance of local information sharing in times of telecommunications disruptions.

3.5.1.2. Borrowing wi-fi: family/friends. Borrowing Wi-Fi from family and friends was the second most salient subcode in this category. Within this subcode, there was a strong trend of people mentioning that they also benefited from the overall use of electricity at the location. This suggests that if we were to expand our search to non-telecommunications-related electricity tweets, we would likely find more examples of people going to friend's and family's houses for electricity, like in Tweet 16:

> Tweet 16: "At my best friend's house, there is electricity & Wi-Fi. #blessed" [2017-10-14]

It was also common to find two layers of adaptations in tweets in this category. For example, Tweet 17 contains one adaptation of a tweeter borrowing Wi-Fi from their grandma, and a second adaptation where the grandma is using a generator to power her Wi-Fi:

> Tweet 17: "The gag is that I'm at my grandma's house borrowing her Wi-Fi from a generator < laughing emoji>and I can't do it at my house < eyeroll emoji>. This electricity problem has me so mad" [2017-11-14]

3.5.1.3. Borrowing wi-fi: school. Schools also played an important role in helping students access telecommunications. Like borrowing Wi-Fi from family/friends, many people benefitted not only from the Wi-Fi but also being able to use the electricity:

> Tweet 18: "I need electricity and wifi at my house, I don't want to keep going to the university Monday to Saturday < vomiting emoji>" [2017-11-30]

In Tweet 18, we see that adapters are going to the school — sometimes during off hours — for the purpose of accessing Wi-Fi. Some people mention explicitly making trips to school to use the Wi-Fi or staying at school longer than they would normally because they do not have Wi-Fi access at home. Wi-Fi access through schools was used for more than just schoolwork. There are several examples in our tweet record of people using the school's Wi-Fi to download Internet content for later use (for both school work and entertainment):

> Tweet 19: "Downloading episodes of the TV show at the University … at this hour the internet is really bad" [2017-12-04]

> Tweet 20: "Tomorrow I am bringing my iPad to download some movies with the University's Wi-Fi." [2017-10-19]

3.6. Charge adaptations

Charge-related adaptations accounted for 281 tweets in our tweet record, making it the smallest among our three modalities. This reduced signal may indicate: (1) that our training data for charge tweets was not as comprehensive; (2) that people were less likely to *tweet* about charging their devices; or (3) that charging adaptations were actually less frequent than adaptations around finding cellular service or Wi-Fi. We hypothesize it is a combination of (1) and (2).

There were eight charge-related codes, with going to another location to charge consisting of several subcodes, and several less-common adaptations falling into the "other" code (See Fig. 7). Of the adaptations within the "other" category, the majority consisted of people charging their devices in the days or hours prior to the hurricane to prepare for the loss of power, or methods to conserve cell phone battery (e.g., low-power mode, airplane mode, deleting apps).

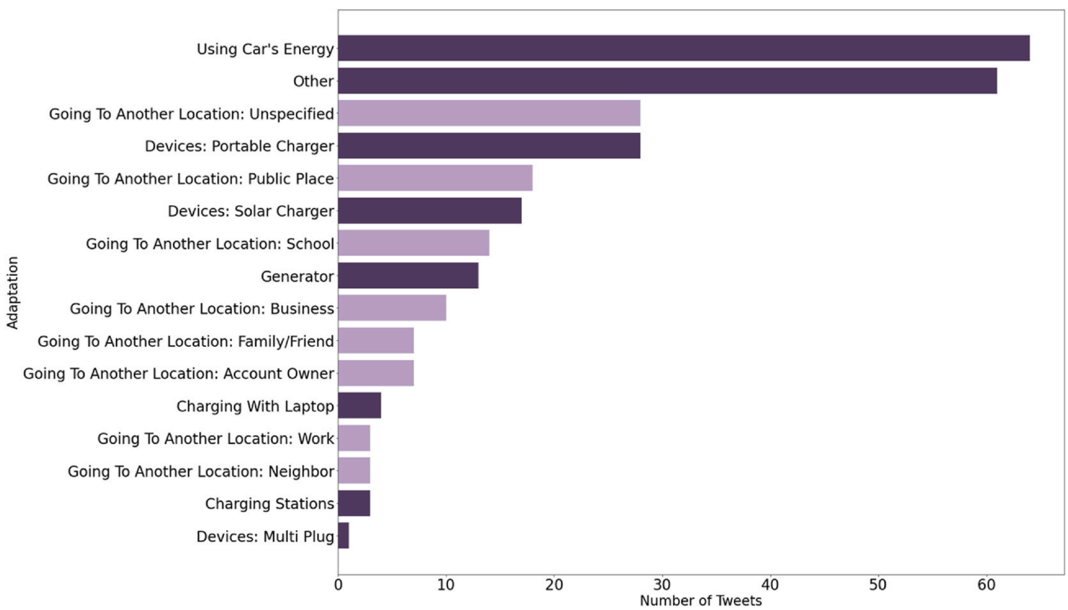

Fig. 7. Number of tweets that are charge adaptations, by adaptation category.

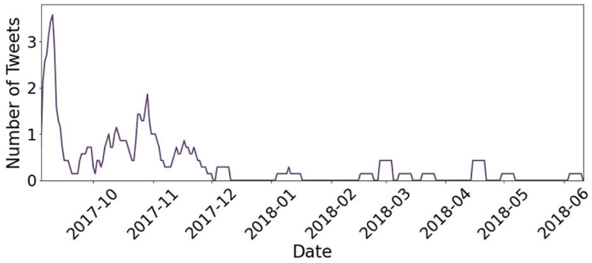

Fig. 8. 7-day rolling average of daily tweets in the going to another location to charge adaptation.

3.6.1. Going to another location

Similar to borrowing Wi-Fi and changing location, going to another location was the largest code within our charge-related adaptations, accounting for 90 (32%) of the total 281. Fig. 8 shows the 7-day rolling average of the daily number of tweets in this category. Unlike the temporal graphs for changing location and borrowing Wi-Fi, this graph peaks much earlier, around Hurricane Irma rather than Hurricane Maria. It peaks again, at a much lower rate, in mid-October and fades away by the early months of 2018.

We separated this category into several subcategories based on where the adapter went to charge their device. The largest subcategory was "going to another location: unspecified". For example, in Tweet 21 the tweeter shares that they were inconvenienced by charging their phone, indicating they had to go out of their way to access electricity to charge, but without noting where they went.

> Tweet 21: "I can't confirm or deny being absolutely freezing from charging my phone" [2018-02-19]

Some example tweets in this category also promote the sharing of resources. In Tweet 22 the tweeter hopes to create a culture of generosity through inviting others to share their electricity:

> Tweet 22: "<Puerto Rican flag emoji> <heart emoji > do what you can no matter how small it may seem

If you have water or electricity.
Give ice.
Invite someone to charge a phone.
Invite someone to wash clothes or shower.
#PuertoRico" [2017-11-01].

This tweet was posted well over a month after Hurricane Maria, highlighting the ongoing need (and ongoing generosity) on the island.

In the following sections we highlight the three most common locations for charging devices: school, public places, and businesses.

3.6.1.1. Going to another location: schools. Schools were a primary location for adapters to charge their devices. Similar to the "borrowing Wi-Fi: school" adaptation (Section 4.3.1), we see that many people went to their school with the primary purpose of charging their phone:

> Tweet 23: "I don't know if I go to the university to study or to charge my phone < shrugging emoji> <laughing emoji>" [2017-11-10]

> Tweet 24: "I don't have classes today, I came to the university to charge my phone" [2017-10-26]

In one example, a tweeter expresses a wish to charge their phone at their school, but being unable to because the university was also experiencing a power outage:

> Tweet 25: "I need a Reese's and for the electricity to return at the university so I can charge my cell phone. <upside-down smiley face emoji>" [2017-11-15]

The date on Tweet 25 is nearly two months after Hurricane Maria, indicating that schools were not always able to serve as consistent sources of electricity in the long term recovery process.

3.6.1.2. Going to another location: public places. Public malls and plazas were a significant source of electricity access as well. Indoor malls also offered the extra benefit of air conditioning:

> Tweet 26: "Here at the plaza charging my cell and getting a/c since I still don't have electricity" [2017-09-12]

In some adaptation tweets, the tweeter does not mention their own adaptation, but takes note of the amount of people using the public malls to charge their phones:

> Tweet 27: "Everyone is in Plaza Las Americas looking for how many plugs there are to charge their things #Yulín [San Juan's Mayor in 2017] You're The Best #PeopleStillDontHavePower" [2017-09-10]

> Tweet 28: "Priorities in Puerto Rico: stores are closed, many people charging phones, tablets and computers #SanPatricioPlaza" [2017-09-08]

These tweets suggest that the primary function of these public places changed after the disaster, becoming sources of electricity rather than shopping centers.

3.6.1.3. Going to another location: businesses. Large companies such as Walmart and Wendy's were popular businesses for charging devices:

> Tweet 29: "Well here at Wendy's charging my phone and I am not leaving until I have 100%" [2018-03-01]

> Tweet 30: "I am going to Walmart for the air conditioning and to charge my phone < annoyed emoji> <laughing emoji>" [2018-03-01]

Both of these examples are on the same date, nearly six months after Hurricane Maria. Although it is unclear whether the tweeters were charging in these businesses due to a power outage related to the hurricane, media accounts describe how efforts to rapidly restore electricity after the storm resulted in a fragile infrastructure [59]. Our data suggest that traveling to other locations to charge devices became a routine activity for many people facing extended and repeated power disruptions.

3.6.2. Using energy from a car

Using their car was one of the most popular methods to charge devices. Car ownership is common in Puerto Rico. With the relatively warm weather, using a car to charge devices also allows the adapter to enjoy air conditioning if their car has that feature:

> Tweet 31: "With the air conditioning on and charging my phone in the truck #comfortable" [2017-09-08]

However, charging phones using a car's energy also drains the car's battery and can cause the battery to die if the engine is not running, which uses gas. Tweets 32 and 33 express that despite this being a popular adaptation, it was still costly:

> Tweet 32: "The 5 days I was without electricity I spent so much money on gas to charge my phone in the car" [2017-09-11]

> Tweet 33: "My phone has 80% charge. I will drive around in my car to charge it more. #IrmaPR" [2017-09-07]

> Tweets 32 and 33 show that while this may not be the most energy efficient adaptation, it may have been the best option for many.

3.6.3. Using specialized devices

Our adaptation tweets revealed Puerto Ricans utilizing a variety of different devices to charge their own devices — or to help others charge their devices.

3.6.3.1. Portable and solar chargers. Portable chargers allow adapters to take advantage of limited electricity by storing multiple charges in a portable charger. Solar chargers are a portable charger that uses the sun's energy to fill their battery. Both portable chargers (generally) and solar chargers (specifically) were mentioned in our adaptation tweets.

Solar chargers were less popular (in our data) than other portable chargers, in part because many tweeters who used solar chargers reported that weather conditions made it difficult to charge them, or that they took too long to charge:

> Tweet 34: "The technology of those portable solar chargers it's about time they give it an upgrade because they take more than 8 hours to charge, damn" [2017-11-16]

Portable chargers, on the other hand, seemed to work well for the majority of adapters. (We saw fewer tweets complaining about them.) However, electricity is needed to power them, which means they can only provide so many charges before the owner has to access power to recharge them. To address this, many adapters used several chargers to extend their battery life, as in Tweet 35:

> Tweet 35: "My fear is that my 3 portable chargers, phone, and speaker run out of battery < crying emoji>" [2017-09-07]

3.6.3.2. Multi plugs. Multi plugs (or power strips) serve to increase the number of outlets from a single outlet. These were particularly useful for those seeking to charge their devices in public places, such as restaurants and public plazas, because they allowed for multiple people to take advantage of a limited number of functioning outlets. The examples of this adaptation in our data also revealed interesting norms developing around the use of outlets in public places, as seen in Tweet 36:

> Tweet 36: "People, if you are going to Plaza Las Americas to charge your phone the least you can do is bring a multiplug so that other people can also charge their phone [with that outlet]" [2017-09-08]

This example highlights both the importance of public electricity outlets after disaster events and also the potential utility of distributing multiplugs/power strips to maximize the public benefit of limited electricity supplies. This adaptation can have downstream effects though, such as over-taxing specific outlets or power infrastructure.

3.6.4. Using energy from a generator

Thirteen adaptation tweets noted that people were using generators to charge their devices. This adaptation surfaced some recurring issues with this adaptation — e.g. multiple tweets in our collection referred to the noise pollution from using the generator:

> Tweet 37: "I hate the sound of the generator, if we didn't need it to at least charge our cell phones it would be gone" [2018-03-07]

Tweet 38 implies that some apartment complexes or households decided to only operate generators at certain times of the day, which was a source of frustration for many who were running low on battery:

> Tweet 38: "Can it be 8 already so that it is time to turn on the generator I only have 9% [charge on my cell phone]" [2017-10-20]

The wide range of interesting dynamics observed around the use and sharing of generators suggests the potential for future research to further investigate these trends.

3.7. Cross-modality adaptations

3.7.1. Technology-based solutions

Several technology-based solutions, such as Project Loon (that aimed to provide Puerto Rico with free internet connection through launching balloons) and apps like Zello (that claim to offer communication without internet or cellular service) appeared frequently in our tweet record. However, they were rarely referenced as successful adaptations.

3.7.1.1. Balloons. Our adaptations data included several tweets about Google's Project Loon [60] bringing internet service to Puerto Rico by using balloons to create an aerial wireless network. Despite the conversations around this innovation, there are no tweets in our collection about anyone successfully using this technology. Rather, all of the tweets we coded in this category were either media reports or advertisements about the services or people asking about how/when they could access the service:

> Tweet 39: "Google: Project Loon has provided internet access to 100,000 people in Puerto Rico via @mashable" [2017-11-10]

> Tweet 40: "@anonymized My house is a black hole of cellular service, where are the Google balloons?" [2017-10-15]

Tweet 39, from a news platform, suggests that these balloons provided internet connection to thousands of people. Tweet 40, posted 25 days after Hurricane Maria, demonstrates confusion about whether and how the technology worked. Taken holistically, the tweets we captured about these balloons demonstrate a discord between the experiences of individual tweeters and the news reports touting these high-tech solutions.

3.7.1.2. Phone apps. 72 of our adaptation tweets mentioned one of two peer-to-peer phone apps (Zello and Firechat) that claimed to provide a way for users to communicate with others during service disruptions. Zello allows for a person to use their phone as a walkie-talkie (communicating with others on the app) when cell phone networks are clogged due to partial service disruptions or in crowded areas. FireChat enables users to communicate with others (peer-to-peer) through their cell phone via a mesh network that combines Wi-Fi (when available) and Bluetooth technology. In the last few years, these applications have been deployed by political activists — including during pro-democracy protests in Hong Kong [61] and the January 6, 2021 insurrection attempt at the U.S. Capitol [62]. In our Maria adaptations data, we saw advertisements for both applications, as well as users discussing their efficacy.

> Tweet 41: "Download Zello Walkie Talkie it is for communicating in case cell phone service stops working" [2017-09-05]

> Tweet 42: "The Zello app doesn't function without internet it is a waste of time < shrugging emoji>" [2017-09-05]

> Tweet 43: "Now I have to delete Zello and download FireChat?" [2017-09-05]

Though the tweet record shows some enthusiasm and willingness to experiment with the apps, at least initially, several tweets (like Tweets 42 and 43) expressed confusion and frustration about the actualities of trying to get them to work. Though Zello was highly advertised in the lead up to Hurricane Maria as a solution to disaster-related outages, it did not work when both Wi-Fi and cell service were completely unavailable [63]. FireChat would work in theory, but an effective mesh network would have required a large number of simultaneous users. We did not see any tweets indicating that users were successfully adapting using these apps.

3.7.1.3. Personal cellular hotspot. Twitter users did post about successfully using another technological solution to adapt (or help others adapt) to telecommunications disruptions: cellular hotspots. Perhaps the relative success of this adaptation is because hotspots are commonly used, not just in times of disaster, making this a more accessible tool for people. There were multiple variations of this adaptation, where adapters would turn on the cellular hotspots on their phone to either share their network with other people's cell phones, or use it to access the internet on their laptop. As in Tweets 44 and 45, this adaptation had many permutations of people who worked together to get a desired mode of communication, including using phones with different phone networks to help others:

> Tweet 44: "I keep using my phone's hotspot from @tmobilepr to connect other people's ATT phones because I have UNLIMITED DATA." [2017-11-17]

> Tweet 45: "*grandpa loans me his laptop* *it takes forever to connect to the cell phone's hotspot* *it connects* *it dies* OH LIFE < upside-down smiley face emoji>" [2017-12-12]

This adaptation also generated a lot of frustration for many people who either got tired of helping others who did not have cellular service:

> Tweet 46: "I should start charging dad for the hotspot" [2017-10-12]

Or even ended with people connected to other's hotspots without their permission:

> Tweet 47: "My neighbor connected to my hotspot for 1 minute. You thought b****, you really f****** thought!!!!" [2017-11-13]

This adaptation captures interesting dynamics between people who had cellular network providers with good connection and those who did not. Oftentimes, the dynamics were negative when hotspots were used without permission or if the behavior became long term.

3.7.1.4. Hotspot provided by company. Many telecommunications companies such as Liberty (a television, internet and phone company) activated free Wi-Fi hotspots throughout the island after the hurricanes. This was a relatively popular, albeit at times frustrating way for people to access Wi-Fi after losing access to their own Wi-Fi networks and/or cellular service. Several tweets even show long term use of these hotspots:

> Tweet 48: "@anonymized I hope so because I miss power and I don't want to keep on going to Liberty for the Wi-Fi hotspot:(" [2017-10-27]

This adaptation also shows examples of adapters sharing information with their followers about where to locate these hotspots, although in many cases it was not clear whether they were sharing this information specifically to help others find the nearest hotspot, or for another reason like in Tweet 49:

> Tweet 49: "Liberty Cable kept in mind all of PR. They put hotspots in Hato Rey, Old SJ, and Luquillo." [2017-10-23]

3.7.1.5. Switching between cellular service and wi-fi. Switching between cellular service and Wi-Fi is a common practice even with functioning telecommunications infrastructure, however several tweets in our record show this adaptation being utilized specifically as a result of the weakened infrastructure after the hurricanes. At times, some people would have to connect to Wi-Fi networks because of decreased cellular service:

> Tweet 50: "@ATT and in my case 75% of the internet is from wi-fi because your internet has been deficient ever since Hurricane Maria …" [2018-02-25]

And at other times the opposite occurred:

> Tweet 51: "It isn't painful for me to use up my phone's battery, because I can just charge it in the car. It does pain me to not have Wi-Fi and waste all my data" [2017-09-08]

Wi-Fi outages could result in cellular network customers with limited data to overrun their data plans.

3.7.2. Social adaptations

3.7.2.1. Informing and adjusting Follower's expectations. One interesting trend in our data was a number of tweets helping the account owner's followers understand what was happening in Puerto Rico and how it might affect their communications going forward. For example:

> Tweet 52: "To all my friends outside PR, we will most likely be out of phone and internet service for the next couple of days #Maria" [2017-09-19]

This tweet, posted just prior to Hurricane Maria striking Puerto Rico, let this account's followers know that they would likely be inactive on Twitter for a period of time. Our adaptations data also contain tweets posted weeks after Maria struck, containing explanations for why the account owner was not able to tweet during the interim.

> Tweet 53: "Family, I am reading it and I don't believe it, I finally have internet to be able to let you know that I am fine and I miss you all terribly < heart emoji> <happy emoji>"[2017-10-05]

This shows an interesting use of the platform, where the adapter can use Twitter to inform a large number of family and friends (and other followers) about their situation in one post, rather than individually contacting each one which could be difficult with only small windows of time with telecommunications access.

3.7.2.2. Learning to live without. Interesting considering our study design limits us to content posted by somehow getting online (onto Twitter), our tweet record includes several examples of people learning to live without telecommunications. Adapters achieved this through finding other methods of communication or simply becoming accustomed to living without it. Tweet 54 shows a user who corresponded with their boyfriend through letters rather the previously used telecommunications methods:

> Tweet 54: "I wrote some letters to my boyfriend since we don't talk because we don't have internet or signal and I gave them to him and his smile was worth gold." [2017-10-13]

Nested within this adaptation are also examples of people who intentionally choose to make the best of their situation by seeing it as an opportunity to get off of social media or focus on their studies:

> Tweet 55: "I think that thanks to Maria and the lack of internet, it will allow me to break my bad habit of using social media. I think I can say goodbye …" [2017-10-29]

> Tweet 56: "It was best if the cell phone service didn't return, I was concentrated on my studies < laughing emoji>" [2017-11-12]

This adaptation demonstrates the resilience of those with long-term connectivity issues who began to adjust to a life with limited communications in a world that increasingly relies on them.

4. Discussion and conclusion

4.1. Insights into telecommunications adaptations

This research provides valuable insights into how people adapt to long-term telecommunications disruptions, enumerating several different adaptations that were prominent in tweets posted by people in an affected area. One thing that stood out in our data was the importance of public infrastructure for supporting adaptations. In particular, we noted an outsized role played by schools as a place for adapting — e.g. charging devices, getting online, pre-downloading content. This may be due to the younger skew of Twitter users in our sample; older people may have used other resources. Private organizations such as restaurants, coffee shops, and large retail stores also provided adaptation opportunities for a large number of Twitter users in our sample.

Another salient finding is the propensity for affected people to travel — sometimes within their neighborhoods or towns, but other times at great distance — to access resources, including better cellular service and Wi-Fi. In an acutely unfolding crisis, this kind of movement can complicate response efforts. And indeed, the tweet record reveals people complaining about traffic congestion from people changing location (traveling to one town from another) to try to find service:

> Tweet 57: "Please fix the service in the Caguas area so that people don't have to come to Bairoa to look for it. The traffic is out of control." [2017-10-31]

Another problematic "changing location" adaptation involved stopping at certain places on the highway to get cellular service. This adaptation was discussed enough in our data to warrant its own category in our coding scheme.

One final observation here is that, though technological solutions such as balloons, and new phone apps received a lot of attention in the media and through promotional messages on social media — our research does not provide much evidence of these being effectively utilized by affected people. Though disasters can be a time where people adopt new technologies [4], it appears that some of these promoted solutions turned out to be too difficult or even impossible to use, e.g., due to a reliance on some of the same disrupted services.

4.2. A concern about social media contagion and adaptations

Our data also reveal people sharing their adaptive processes with each other through public social media platforms, in this case where to find service [19]. note how adaptations by individuals can compound and become problematic at scale. Social media may exacerbate this dynamic — e.g., through "viral" trends that shift adaptive behaviors at scale. In a longer-term crisis (like Hurricane Maria), disaster responders and communicators may want to incorporate considerations of these dynamics into their plans.

4.3. Using social media to understand adaptations at scale

Our research also demonstrates the utility of using social media data to uncover disaster-related adaptations. This contribution aligns with existing work by researchers in crisis informatics (e.g. Ref. [5], but expands that body of work, which initially focused primarily on impacts, to include how affected people are changing their behaviors to adapt to those impacts. This approach may be useful to other researchers of human behavior during disaster events — to enhance our understanding of collective responses to disaster-related disruptions. Through future research along this vein, emergency responders could benefit from using social media data to better understand, perhaps eventually in real-time, how people are adapting to the impacts of an event — and use this knowledge (e.g., on how demands on the infrastructure are changing or how people are engaging in potentially dangerous adaptations) to adjust their response and communication strategies accordingly. In particular, our approach to identifying and understanding adaptations to disruptions may be valuable when used in combination with approaches for automatically detecting disruptions to critical infrastructure [15,16]. Bringing a societal-level perspective on the problem [64], offer an integrated, interdisciplinary framework for connecting the operations of a critical infrastructure, user needs, and both operator and user adaptations to understand overall societal impacts from losses. Insights from social media may provide real-time input for assessing the societal impact of adaptations.

One challenge for integrating social media data into our understanding of disaster impacts and responses — for researchers as well as crisis responders — is the "needle in a haystack" issue. Even for this study, where we were able to home in on tweets posted by people who were likely in Puerto Rico during the aftermath of Hurricane Maria, only a tiny percentage of tweets contained information about adaptations. Identifying those tweets is difficult. Our work provides one approach for training machine learning models to achieve this.

To identify adaptations, we first developed and employed a human-in-the-loop approach for using machine learning to identify signal within an extremely noisy dataset of textual content. Adaptations constitute only a tiny proportion of overall tweets, even among an affected population. To find them, we began with a deductive keyword-based search to develop an initial training dataset, adopted an "active learning" approach through which we manually coded and expanded that training dataset, then used machine learning — in this case an RNN model with pre-trained embeddings — to automatically code a massive dataset, and finally validated a portion of the coded data with human coders. In Fig. 3, we map the adaptation tweets over time by modality and demonstrate close alignment with external data documenting power outages in Puerto Rico — providing some support for the validity of this method. However, we acknowledge that differentiating between impacts and adaptations using a machine learning approach remains a challenge. (In our evaluation of the model and our qualitative analysis, we relied on human coding to distinguish between the two.)

4.4. Limitations and future work

Our work has several other limitations. At its very core, this research relies on social media trace data that have biases that are both known and unknown. Social media data are known to be more useful for gathering information about large and high-visibility events

[8] — like the event featured here — and less useful for smaller and lower-visibility events. Additionally, the proliferation of rumors, misinformation, and disinformation may reduce the credibility, and therefore the utility in a safety-critical context, of social media data. Another complexity is that the population studied here may not be fully representative of the target population (i.e., the general public), meaning insights about human behavior during disasters drawn from these data are likely to undercount or even overlook entirely behaviors by people who were less likely to be social media users (in this case, individuals who are older, more rural, less wealthy). Similarly, access to Twitter implies internet access, meaning we do not have data — or insights into adaptations — from those who were unable to connect. This form of survivorship bias means we are likely missing the voices and experiences of those who were most severely impacted by the disaster, further limiting external validity of our findings. Our analysis suggests that these social media data were also biased towards containing adaptations related to the technologies used to post on those platforms — in other words, people trying to tweet seem to be more likely to mention how they managed to get Wi-Fi than how they are coping with other disaster impacts (like water disruptions). In future work, we aim to apply this method (and assess its utility) to investigate other kinds of adaptations.

In terms of methodological limitations, our initial approach to finding signal in the noise, which relied on keyword-based searches to identify an initial training dataset, may have led us to find more of what we were already expecting and less of what we did not know to expect. Though that concern is valid, our machine learning model identified (as adaptations) tweets that did not contain any of the terms we used for our initial coding, and the broader process surfaced several adaptations that surprised our research team. Another limitation regarding the model is that only ~40% of the adaptations that were classified as ≥90% probability of being an adaptation were actually adaptations. This means that the model must still be aided with manual coding to eliminate noise, albeit on a significantly smaller sample than would be the case with less sophisticated approaches (e.g., keyword searches). Finally, the model we chose (RNN) works best on syntactically and semantically homogenous datasets. Due to the extensive linguistic diversity seen on social media, this is a limitation to using this type of model on Twitter data.

Simply looking for content about adaptations may only get us part of the way towards measuring how widespread they are among specific populations (e.g., geographic) at certain times. Here, we introduced the concepts of positionality and temporality in tweets, and provided a few examples hinting towards their utility. Positionality is valuable for understanding who is adapting and temporality is important for determining if and when an adaptation happened. As we consider measuring the use and effects of adaptations at scale, accounting for positionality and temporality will be necessary. In future work, we hope to provide a deeper analysis of these dimensions — including how they intersect with other codes (such as service and adaptation type).

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Some data may be made available upon request.

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Appendix

Appendix A. Methods for Study 1

Data Collections

The data collection process involved two distinct steps. First, we created a "keyword dataset" (Step 1, Fig. 1), using Twitter's Streaming API to collect tweets with Hurricane-related terms during the warning and acute impact period of Hurricane Maria — from August 24 to November 6, 2017. Collection terms included *maria, puerto rico,* and *puertorico.* This collection ran in real-time and resulted in ~30 M tweets. Next, building off the keyword dataset, we generated a "user contextual stream dataset" [32] for users we determined to likely be "local" to the event — including accounts with "Puerto Rico" in the profile description or location fields (40, 906 accounts) and accounts with tweets with embedded geolocation information that placed them within Puerto Rico during the initial collection period (2882 accounts). After identifying these accounts, we attempted to collect all the tweets each account posted leading up, during, and for several months after Hurricane Maria struck Puerto Rico. We did this using the Twitter REST API to capture the most recent 3200 tweets for each account on four occasions: in January, February, April, and June 2018. The analyses presented here focus on this user stream dataset, which runs from September 1 (as Hurricane Maria was beginning to take shape and just prior to Hurricane Irma striking Puerto Rico) to June 1 (more than eight months after Hurricane Maria came ashore). This dataset contains 55

M tweets from 41,485 “local” accounts. Approximately 19 M of these tweets were “original” tweets (not retweets), and — to reduce noise and limit our focus to content produced by “local” accounts — our analyses focus on those 19 M original tweets. We will refer to this dataset of 19 M tweets as the *Hurricane Maria Local's Original Tweets Dataset.*

Initial training data

Our *Hurricane Maria Locals' Original Tweets Dataset* contained a massive amount of noise — i.e., all the other things, from pop music to politics to everyday happenings, that people in Puerto Rico tweeted about during the months following Hurricane Maria. Only a tiny percentage were related to adaptations to telecommunication impacts from the disaster, which we confirmed through an initial, qualitative analysis of several samples of data.

To begin to home in on the signal within that noise, we employed an iterative method detailed in a preliminary paper [51]. This method consisted of a top-down, heuristics-based approach to identify a sample, followed by a bottom-up, grounded approach to expand the sample to include a broader array of cases. This took place through an iterative process of testing queries that were likely to generate a low noise sample of adaptations, then branching out with additional queries from new adaptations discovered from previous queries. Initial queries included combinations of search terms that we identified through examination of previous literature on adaptations (e.g., terms like “generator”), as well as terms that emerged as relevant to our research questions through earlier rounds of qualitative analysis (open coding) of random samples of data (See Appendix D for a full list of terms.). The final result of this was a 30 queries that generated a dataset of 6482 tweets which were manually coded to find 1900 tweets with adaptations to telecommunications impacts.

Machine Learning

Next, we used this sample of adaptations-related tweets to train a Recurrent Neural Network (RNN) machine learning model to identify additional adaptation tweets in our *Hurricane Maria Locals' Original Tweets Dataset*.

Model Input and Data Preprocessing

Our model input has four parameters. Although the primary parameter of interest in our model is the text field, we added three more parameters: the date, whether the tweet contained a link, and whether the tweet was directed at another user (through a @mention or reply). Based on our previous research, we knew that the adaptation tweets are not distributed uniformly in time throughout our collection period (8/31/17–6/18/18). For this reason, we turned the date and time of the tweet into a proportion such that 0.0 and 1.0 corresponded to the first and last tweets in our dataset, respectively. We also added a binary variable that took on two values based on whether the tweet was directed at another user or not. For example, of all the tweets that were classified as being an adaptation because they were tweeted at a mobile phone or Wi-Fi network provider, this feature has the ability to learn that these tweets are positive (i.e., likely adaptations) and classify future similar tweets as positive. For the same reason, we added a binary indicator for whether the tweet contained a link or not. For the text field, we made all of the text lowercase, removed the Spanish language stopwords (common words that can be filtered out i.e., ‘the’, ‘it’, etc.), removed punctuation, and lemmatized (removing the conjugation of the word so that different conjugations are the same i.e., ran and running → run) the tweet.

Preliminary Training Data

Our preliminary data consisted of 1900 adaptation-related tweets from our preliminary research on adaptations to telecommunication disruptions [51]. We added 1900 tweets that did not contain a telecommunications adaptation, which were obtained from a random sample of our *Hurricane Maria Locals' Contextual Streams Dataset* then manually coded to determine that they were truly negative. We then expanded our data to include adaptations (not investigated in the initial research) related to charging a communication device — such as a phone or laptop. For this step, we used the same query-based approach to identify and add 500 charge-related adaptations to our training data, which we further balanced with an extra 500 negative tweets.

The resulting dataset — our *Initial Training Data* — consisted of 3800 tweets, with 50% tweets that were positive (adaptation) and 50% tweets that were negative (non-adaptation). This is not proportionally representative of the broader dataset, which we estimate to be far less than 1% adaptations, however we chose a balanced training set in order to include as many positives as possible for the model to use for training.

For the purpose of this study, we do not add tweets that are solely impacts (but not adaptations) to our training data as either positives or negatives. This is because the language in impact tweets and adaptation tweets can be so similar that we risk the model learning to classify adaptations as negative if we train it on negative impacts.

Testing Data

We tested our models on two datasets: one random sample (from the 19 M original tweets in the *Hurricane Maria Locals' Contextual Streams Dataset*) of 1000 tweets and another of 100,000 tweets. For the random sample of 1000 tweets, 995 were negative for adaptations, and five were positive. We used this test data to obtain performance metrics for different models.

We used the random sample of 100,000 tweets to get a sufficiently large sample of positive tweets (but not so large that we could not manually inspect them all) so we could see what keywords were triggering false positives. We manually coded all of the tweets that were labeled as likely adaptations as to whether they were actually adaptations, were related to disaster impacts but not adaptations, or were not related to the disaster. We used the false positives — i.e., tweets that the model classified as likely adaptations but turned out to be either impacts or not related — to calibrate the training data (described in more detail, below).

Evaluating our Model

Using our machine learning classification model, the output for each tweet is a binary classification P with a classification threshold of 0.5: $P \varepsilon \mathbb{Z}$: $P \varepsilon \{0,1\}$:0 if $p \varepsilon [0, 0.5)$; 1 if $p \varepsilon [0.5, 1]$ where $p \varepsilon \mathbb{R}$: $p \varepsilon (0,1)$ is the prediction. However, when we run the model over the entire dataset at the end, the prediction is a real number probability $p \varepsilon \mathbb{R}$: $p \varepsilon (0,1)$ of the tweet being an adaptation. This allows us to sort our results according to the probability prediction within different intervals — i.e. tweets that are determined by the model to be more or less likely to be adaptations. We use the confusion matrix and the F1 score to evaluate our model. The F1 score, given by: $F_1 = \frac{2 \bullet precision \bullet recall}{precision + recall}$, where

$$precision = \frac{true\ positives}{true\ positives + false\ positives}$$

and

$$recall = \frac{true\ positives}{true\ positives + fase\ negatives},$$

equally weighs precision and recall, which is necessary due to the highly imbalanced nature of our data (lots of noise, very little signal). Using accuracy would falsely overstate our model's performance — because the score would still be high even if the model missed every adaptation due to the proportion of adaptations in our data being so small.

Improving our Training Data through an Adapted Active Learning Approach. To improve the performance of our model, we used a supervised learning process — adapted from an active learning approach [55] — to expand and refine our training data. This process took place through four phases and was designed to reduce the false positives (non-adaptations classified as adaptations) and false negatives (adaptations classified as non-adaptations). To reduce the number of false negatives, we manually identified new adaptations in a random sample of 100 of the tweets that the model classified as likely-related (≥0.9) and added additional positive examples of these to the training data. To reduce the number of false positives, we inspected the tweets the model classified as likely-related and found keywords that were appearing often and were likely to pick up noise. For example, our training data contained several examples of people charging their phone in their car, and so the model classified any tweet with the word "car" ("carro") in it as likely-related. To remedy this, we queried our *Hurricane Maria Locals' Contextual Streams Dataset* to identify and add negative examples of tweets containing these words.

In the final phase of calibrating our training data, we eliminated the adaptation where someone is reaching out to their telecommunications provider regarding a service outage from our training data. Although this is a noteworthy adaptation, this was the most common adaptation being picked up in our 100,000 tweet dataset, and it was drowning out the other adaptations.

Calibrating our training data greatly reduced the number of false positives in our model, while not having a negative impact on the number of true positives. To help provide an understanding of how this process works, Table A-1 (right) shows the impact of calibrating the training data on the 1000 tweet test set. Table A-1 (left) shows the performance for the 100,000 tweet set before and after calibration (left), which were obtained by manually coding all of the tweets in each of the following intervals: [0.7,0.8), [0.8,0.9), and [0.9,1.0], to determine the percent that were adaptations, impacts, or not related. (Because impacts are so close, linguistically, to adaptations — we added "impacts" in the evaluation phase to quantify how our adaptation classifier often identified impacts rather than adaptations.)

Table A-1
Performance metrics for RNN with pre-trained embedding before and after adding new terms to training data

	100,000 tweet dataset			1000 tweet dataset			
	[0.7–0.8)	[0.8–0.9	[0.9–1.0]	Accuracy	Precision	Recall	F1 score
Initial training data	44	77	468	0.994	0.625	0.625	0.625
Adaptations	9% (4)	14% (11)	15% (70)				
Impacts	18% (8)	16% (12)	31% (145)				
Not related	73% (32)	70% (54)	56% (262)				
4th phase of training data	37	51	130	0.999	0.833	1.000	0.910
Adaptations	5% (2)	6% (3)	42% (54)				
Impacts	41% (15)	37% (19)	36% (47)				
Not related	54% (20)	57% (39)	22% (29)				

Focusing in on the [0.9–1.0] range, the tweets labeled with the highest likelihood as being adaptations, can provide insight into the benefits of calibration. In the initial model, though 468 were labeled as likely adaptations, manual coding revealed that 85% of that was noise (either impacts or not related). Whereas in the final model, though the overall number of adaptations found were slightly fewer, the noise was significantly reduced, yielding 42% adaptations, 36% impacts, and 22% not related. The discrepancy here between the model's 90% confidence rating and much more modest (42%) results is largely due to conflating adaptations and impacts, which are highly similar and difficult (even for human coders) to differentiate.

Choosing a model. We tested multiple models, optimizing on the F1 score and the model we chose was the recurrent neural network (RNN) [52] with pre-trained word embeddings [53], which resulted in an F1 score of 0.778 with our initial training data. Pre-trained word embeddings are vectors that correspond to each word in a language such that words with similar meanings are closer to each other in the vector space. A neural network mimics the thought process of the human brain through implementing nodes that generate "decisions" (based on probabilities) of the input's classification [65]. The RNN is a variation on this, where the training process also takes into account previous inputs in the hidden layer (where the input is transformed into data the model can use to make a decision) to build context for better classifications. The pre-trained word embeddings are obtained by training on large datasets, then saving the vectors for use in other algorithms. For our model, we use the embeddings from fasttext. cc which were trained on Spanish-language Wikipedia articles.

Appendix B. Positionality Coding Scheme

Cohen's Kappa: 0.64 (moderate agreement).

Table B-1
Codes, Definitions, and Examples for Positionality

Positionality	Definition	Example
Adapt myself	The adapter is doing something to adapt to a disruption that they are experiencing.	"When will be the day that I don't have to leave my house to look for a signal"
Adapt ourselves	A group is adapting to a disruption that they are facing as a group.	"The plaza is full cc and we are all doing the same, getting air, signal, and charging phones"
Some people are adapting	The account owner is tweeting about the adaptive actions of another person or group which they themselves are not doing.	"Please fix the signal in the Caguas area so that people do not have to come to Bairoa looking. The traffic is now out of control"
Someone is helping me adapt	Someone is helping the tweeter adapt to a disruption that they are experiencing.	"@reply because I left from my house to my grandma's, but now I have to return back to my house where I do not have signal nor wi-fi:)"
Helping someone adapt	The tweeter is helping someone else adapt to a disruption.	"If you need Internet in Mayagüez to communicate with family, please write an inbox. We are giving access in town"
Information seeking	The tweeter is seeking information about actions they can take in order to adapt in the near future.	"Where in Guaynabo can I get Wifi?"
Information sharing	The tweeter is sharing information to help others who have lost access to communicate.	"Tremendous scare #HuracanMariaPR Manatí by the Petra, CLARO has very good signal LTE so you can communicate with relatives"
Sell a service	A party is trying to sell a product or service for profit to a person so they can adapt to a disruption.	"Everyone will want to connect to your network with the free HotSpot that Claro's plans have. Switch today! #TheMostPowerfulNetwork"

Appendix C. Temporality Coding Scheme

Cohen's Kappa: 0.45 (weak agreement).

Table C-1
Codes, Definitions, and Examples for Temporality

Temporality	Definition	Example
In progress	The adapter is in the process of doing the adaptation. They are tweeting about it at the same time as they are adapting.	"Being in the traffic on the highway no longer bothers me because I finally have signal"
In progress: habitual	The adapter is implying that they have adapted and are continuing to adapt in this way, such that it has become a routine and may be an adaptation for the long term.	"Catching signal from time to time to know if our own are still here in PR, transiting through the streets is … "
Future/ hypothetical	The tweeter is mentioning an adaptation that may occur in the future or is hypothetical.	"I'm officially moving to San Juan, I have signal here ♥ <heart eyes emoji>"
Past	The tweeter is implying that they did an adaptation in the past but are no longer doing it because it may not benefit them anymore or they just are not doing it at the moment because they are not needing it.	"I charged my phone in the car. <laughing emoji>"
Preparatory	The tweeter is implying that they are not experiencing a disruption but are preparing themselves by preparing an adaptation for the future.	"Mood: charging the phone from today < face palm emoji>"
Unclear/ Multiple	The tweeter implies that there is a possible adaptation but there is no clear signal of when the adaptation occurred and/or the tweet could be interpreted in two or more temporalities.	"To say that I am going to Isla Verde for 30 min using the internet is the equivalent of saying that I will only go out to give myself "2" beers.."

Appendix D. Coding and Arbitration

1st level arbitration: If the first two coders did not agree on the relevance, then it went to a 3rd coder randomly selected from the 2 coders who had not previously coded that tweet. The 3rd coder only codes the first level. There were 3 potential outcomes of this.

1. **Arbitrator agrees with one of the two initial coders, *and* does not code it as an adaptation:** The tweet is determined to be whatever the arbitrator coded it as, and is done being arbitrated
2. **Arbitrator agrees with one of the two initial coders, *and* codes it as an adaptation:** The tweet is determined to be an adaptation. *The tweet is returned to the initial coder who said it was not an adaptation, and they are forced to code it as an adaptation.*
3. **Arbitrator does not agree with either of the two previous coders** The tweet is discussed as a group where we all decide on the code:
    1. If the group decides it is not an adaptation, then the tweet is done being arbitrated, and the group decision is the final code for the tweet.

2. If the group decides it is an adaptation, then it is determined to be an adaptation then it got sent back to the first one or two coders that did not think it was an adaptation (could be one or both of them) and they are forced to code it as an adaptation

2nd level arbitration: The second level arbitration is only completed after a tweet is either determined to be an adaptation because it falls into the following categories: **(i) the first two coders agreed it was an adaptation (ii) only one of the first two coders said it was an adaptation *and* the tweet was arbitrated by a third person who said it was an adaptation (iii) the tweet was moved into the group arbitration phase and was determined to be an adaptation by the group**. In options 2 and 3, the tweet will be sent back to one or both of the first level coders who said it was not an adaptation who will be forced to code it as an adaptation. The result is every tweet that is determined to be an adaptation has 2 sets of codes in the second level of categories. If after achieving 2 sets of codes as adaptations they disagree in one or more columns, the tweet is arbitrated at a second level.

A randomly selected coder who was not in the first two coders to code the tweet is presented with a sheet with the tweet, and both of the first two coder's codes in each column. If the two codes agree from the first two coders, the third coder does not do anything and moves on: the final code is the one the two initial coders agreed on. If the codes do not agree, the 3rd coder chooses which of the two codes they prefer, and selects that one. The options they choose are considered to be the final codes for the tweet.

Appendix E. Search terms for Creating Initial Training Data

	Terms added or removed
Initial Training Data	Original (Spanish): "amig" + "wifi", "biblioteca" + "internet", "biblioteca" + "wifi", "busca" + "internet", "busca" + "señal", "busca" + "wifi", "caguas" + "señal", "camin" + "señal", "chapia" + "señal", "chapia" + "wifi", "claro" + "señal", "conseguir" + "señal", "conseguir" + "wifi", "donde" + "wifi", "encontr" + "wifi", "escuela" +"internet", "escuela" + "wifi", "mejor" + "señal", "muda" + "señal", "para tener wifi", "para usar el wifi", "proveedor" + "cambia", "roba" + "wifi", "san juan" + "señal", "starbucks" + "wifi", "techo" + "señal", "viaja" + "señal", "voy a" + "para" + "señal", "voy a" + "para" + "wifi", "wifi" + "vecin" English Translation: "friend" + "wifi", "library" + "internet", "library" + "wifi", "look for" + "internet", "look for" + "service", "look for" + "wifi", "caguas" + "service", "walk" + "service", "steal" + "service", "steal" + "wifi", "claro" + "service", "get" + "service", "get" + "wifi", "where" + "wifi", "find" + "wifi", "school" + "internet", "school" + "wifi", "better" + "service", "move" + "service", "to have wifi", "to use the wifi", "provider" + "change", "steal" + "wifi", "san juan" + "service", "starbucks" + "wifi", "roof" + "service", "travel" + "service", "I am going to" + "in order to" + "service", "I am going to" + "in order to" + "wifi", "wifi" + "neighbor"
Phase 1	**Negative Examples**: "internet" ("internet"); "wifi" ("wifi"); "señal" ("service"); "carro" ("car"); "techo" ("roof"); "celular"/"cel" ("cellular"/ "cell"); "planta" ("generator"); "claro" ("clear/simple", network provider); "servicio" ("service"); "chapiar" (slang "steal/get/use"); "vecino/ a/os/as" ("neighbor/s"); "cargar/cargador" ("charge/charger")), "AEEonline"
Phase 2	**New Adaptations:** "Zello" (app); "firechat" (app); "multiplug"; "multi plug"; "globo" ("balloons"); "balloon"; "sistema solar"
Phase 3	**New Adaptations: "**Manifestación" + "AEE" ("protest" + "AEE"), "protesta" + "AEE" ("protest" + "AEE"), "protesta" (for negatives), "bateria" + "9v"/"batería" + "9v" ("battery" + "9v"), "ahorro de bateria"/"ahorro de batería" ("battery save"), "walkie talkie", "wifi gratis" ("free wifi"), "lista" + "servicio" ("list" + "service"), "compart" + "internet" ("share" + "internet"), "hotspot"/"hot spot", "placa" + "solar" ("solar" + "panel") **Negative Examples**: San Juan, Ponce, Caguas, computadora, buscar, pr, puerto rico, app, google, netflix, calle, viajar, escuela, hospital, plaza
Phase 4	**Changed:** tweets that were directed at electricity/network/internet providers to make them aware of an interruption in service to negative + deleted some examples to not bias negative examples.

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