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# Vulnerable populations and social media use in disasters: Uncovering the digital divide in three major U.S. hurricanes

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ABSTRACT

How populations use social media in disasters is essential for evaluating the representation of subpopulations while analyzing social media data for emergency response and disaster research. Existing machine learning models can extract, characterize and make sense of digital trace data from social media, but are unable to account for diversity in population groups and use of social media. Consequently, the reliability of their decision-making ability remains questionable. This paper presents an exploratory analysis of empirical household survey data on the information seeking, sharing activity, and perceptions of information reliability on social media platforms across different population groups during three major hurricane storm events in the United States between 2017 and 2018. The results of this analysis suggest significant associations between social media use and socioeconomic factors: (1) Socioeconomic factors along with geographic effects play a role in determining not only platform uptake but both motivations for information seeking and the action of information sharing on social media, (2) The type of social media platform influences the type of information people seek, (3) Households from lower socioeconomic and minority backgrounds were more likely to use social media platforms to sought out different information on social media than their peer, (4) perceptions of information reliability are also influenced by social divides, where households in rural areas, lower income groups, and racial minorities were more likely to report greater unreliability in social media information. These findings provide new insights into the roles of social media use in creating or dismantling the digital divide during disasters.

## 1. Introduction

During Hurricane Harvey, first responders witnessed unusual activity on social media by individuals seeking assistance due to overloaded 911 calling systems [1]. In addition to contacting for emergencies, the general public turned to social media for situation awareness (information checking) [2,3], information sharing [4], rescue coordination, and volunteer efforts. According to the Structural Influence Model of Communication (SIM) [94] applied in health disparity research, any differences among social and racial-ethnic groups in the use of communication channels, such as social media platforms, could result in both an indirect and direct effect on risk exposure and impact in the context of health outcomes. As a result, existing disparities among vulnerable groups can be exacerbated due to differences in social media access and use [5,6,96]. In disaster situations, it is not likely to be very different as “the fundamental issues of inequality and stratification at the heart of sociology are usually at the margins of communication studies” [7].

While social media platforms (Facebook, Twitter, Nextdoor) have become powerful tools used by the public to cope with disasters, researchers in the field are becoming acutely aware of the potential population biases and misrepresentations [8] inherent to digital trace data from social media platforms. Machine learning techniques have been applied to classify and characterize data from social media in the context of disasters and analyzing the nature of information dispersion and networks during disasters [9–15]. Some research has used social media data (such as tweets) to determine social media usage disparities. Their conclusions suggest that because certain population groups are not active on social media during disasters, based on their metrics, they are at greater risk due to communication gaps [16,17].

Differences in population representation across social media platforms are well-documented in research conducted over the last decade from gender representation [96] and across factors such as race, ethnicity, and parental educational background [18]. Several studies

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have recognized the presence of population bias in digital trace data from Twitter and its problematic implications [19–21]. Social and demographic factors have been found to influence preferences for social media platforms [19,21,97]; as well as the use of platform mechanisms [22]. However, a significant pitfall of machine learning algorithms for social media data is that they tend to assume uniform usages of social media across population groups and accurate representations of the target population. Making such assumptions not only misrepresents certain groups of users but also influences the performance of various prediction models [23]. Therefore, research outcomes are at risk of informing discriminatory decisions [22], which is in complete contradiction to an overarching goal to achieve social equity and remove barriers and disparity in disaster recovery and resiliency of communities.

Similarly, the digital divide due to uneven access to social media platforms and different motivations for social media use can distort the situational awareness created during disasters [13] and lead to significantly underestimated needs of the population and compromise the external validity of research and performance of algorithms that make inferences about social media data [22]. There are further concerns over the reliability of the information derived from social media sources [24,25]. As a result, decisions made based on models and studies using data with skewed population representation can result in unintended outcomes such as disparities in the emergency response and protection of disaster victims in a given area [6].

To date, few empirical studies exist which rigorously document the digital divide in social media and the user experience during situations like a disaster [26,98]. Conversely, research has been geared more towards the needs of emergency response workers [12,27] and organizations [28] in terms of using social media data to make decisions and less on the users that are creating content and developing tools to manage social media data and how software can better support the social media needs of emergency managers [12]. Eismann et al. [29] conducted a systematic literature review on collective behavior in social media in disaster situations, finding that disaster characteristics do, in fact, collective influence behavior in social media in response to the respective disasters.

## 2. Research scope

More robust methodological investigations about the nature of population representation in social media are needed to produce an empirical understanding of digital divide issues [30,31] related to experiences during disasters. This paper builds upon existing research of social media bias and inequality by examining the social and geographic factors influencing the digital divide in different areas impacted by a crisis. Cross-sectional data on the use of social media platforms (Facebook, Twitter, Nextdoor) by different population groups in the aftermath of three major U.S. hurricanes occurring between 2017 and 2018 (Harvey, Florence, and Michael) was collected through three separate household surveys. Using descriptive statistics, ANOVA testing, and fitting regression models, an analysis of social media uptake, social media platform use, social media behaviors and purpose of use, and information reliability across social groups and locations impacted is presented.

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

(1) To what extent do information sharing and seeking behaviors differ across different social groups and geographic locations?
(2) How does the perception of social media information vary by different social factors and platforms?
(3) To what extent is the social media platform associated with the information people seek during disasters?
(4) To what extent social media use vary across different disaster-afflicted regions (i.e., Harvey vs. Michael vs. Florence) and urban versus rural settings?

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

## 3. Background

### 3.1. Disaster communication and social media

Communication is central to facilitating community resilience during disasters [32–34]. A disaster can be traced back to a crisis in the communication process or the result of a communication breakdown [35]; p. 479). Mass mediated disaster communication generally consists of disaster warning messages and mass media news coverage of disasters disseminated through official government organizations on the radio or television. Rodriguez et al. [35]; p. 482) contend that mass media coverage of disasters' has a significant influence on how people and governmental organizations perceive and respond to disaster events [35]; p. 479). Hence, disaster communication has the power to influence individual disaster knowledge, attitudes, and behavior, which control one's "situation awareness." Situation awareness is defined as "all knowledge that is accessible and can be integrated into a coherent picture, when required, to assess and cope with a situation" [36]. During disasters, traditional media and other communication channels are often unavailable, lack timely response, and insufficient given the urgent needs of those seeking information [37]. At the same time, mass-mediated coverage of disasters through traditional channels is limited in that it usually involves messages created by a single source and disseminated to large audiences, with little opportunity for audience response and participation.

Web-based social media has become an influential platform for disaster communication and has been considered advantageous over traditional media outlets [32]. Compared to traditional media, web-based social media technologies have greater capacity, dependability, and interactivity, which would help enhance disaster communication. Social media also has advantages in information flow, information control, adaptability, relevance for residents, intelligence, empowerment, dependency on the power grid, cost, accessibility, and timeliness of information [38]; p. 52). As a result, social media platforms have become critical spaces for situational awareness, or people to receive and share information about events unfolding [39]. A key advantage the platforms offer is delivering real-time emergency information to the affected people on time [40]. Having timely access to factual information is crucial for actors to learn what is happening on the ground [41,42]. During earthquakes and floods, providing and receiving information about disaster response activities and opportunities using social media is highly cited as recognized by Ref. [43]. Social media has been used to communicate warnings [43–46] and preparedness information [45,47], raise awareness of the disaster and promote fundraising [47,48,105], and seek and provide emotional support [47]. [32] introduced a disaster social media framework of users and uses based on a comprehensive literature review. Their paper thoroughly discusses the various types of users (organizations, individuals, communities) active on social media during a disaster and the users' various uses of social media. It illustrates the variety of entities that employ and produce disaster social media content.

While advantageous for real-time situation monitoring, the "avalanche" of data is a common pain-point for emergency response and humanitarian relief organizations interested in using information derived from social media platforms [49]. Data from social networks is noisy: most social media posts do not include new or useful information and unverified, where many repeat information that is already available through other channels. Filtering through the mass amount of information is overwhelming [50], and as a result, impractical for agencies to make use of for real applications [51].

### 3.2. Social media platforms: Facebook, Twitter, Nextdoor

At present, various social media platforms are used in disaster-related communication, including popular platforms such as Facebook, Twitter, and Flickr [28,39], but also disaster-specific applications [52]. Social media characteristics can help explain the structure and functions of interactions that take place on specific platforms [53]. For example, Facebook and Twitter have different text limitations and features for posting information, which controls how users interact on the platform's space. Kane et al. [53] identified four primary features of all social media platforms which help to distinguish them from one another: (1) The degree to which the platform allows unique "digital profiles" or user profiles, (2) The platform's "search and privacy" mechanisms which control how users access content on the platforms, (3) How users build and develop "relational ties", (4) How the platform allows "network transparency."

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

#### 3.2.1. Twitter

Twitter is the social media platform referred to most often in disaster and crisis informatics research [15] and is often used to exchange disaster-related information by all social units in all disaster categories. It is beneficial for disaster relief professionals as it is easy to use and monitor, facilitates quick information dissemination, and can be updated anywhere [54]. Based on a review of literature, Twitter has been used for various protective action and disaster response efforts, including warnings [44,45,55], situational awareness updates [44,46,48,56–59]. Twitter is also used for functions that require two-way communication [58]. Such as inquiring about another's well-being [55,58] and discussing events and their consequences [58,103,116]. An advantage of Twitter as a social media platform is its feature of sharing short messages and the ability to publish direct and indirect updates [58]. Twitter has shown to be useful in reporting breaking news [99,117], in some cases, faster than mainstream media outlets [107].

#### 3.2.2. Nextdoor

Nextdoor is a hyperlocal social media platform that connects its members based on geography, a unique relational tie, and network transparency feature not part of Facebook or Twitter's platform capabilities. Unlike Facebook or Twitter, the process for creating a Nextdoor account is less straightforward. Users must register using a verified address and are connected with nearby users based on geocoded addresses. In recent disasters (such as Hurricane Harvey), Nextdoor was used by residents to communicate and coordinate relief and rescue efforts in neighborhoods [1]. Recognizing how their platform can be a helpful tool during disaster situations, the official website of Nextdoor details how users of the platform can take advantage of the platform's features to get help and stay safe during hazardous situations. The above evidence shows that different social media platforms are being used in disasters. However, little is known about the extent to which different sub-populations use these social media platforms and how they use it. This understanding is essential for public officials and emergency managers to utilize social media during crises effectively and also for researchers to examine better data obtained from the different social media platforms [60].

#### 3.2.3. Facebook

Relative to Twitter, Nextdoor, and other existing social media platforms, Facebook is considered more "static" [58] and offers a broader audience base while enabling longer messages. In general, it is preferred for functions that require longer text messages and active communication. On this platform, the functions that prevail include relief coordination, keeping in touch with others, discussing events and consequences, and seeking advice [37]. Bird et al. [61] argue that Facebook (p. 32) "can be used to effectively and efficiently disseminate emergency information on the occurrence of hazards; location of evacuation centers and road closures; fundraising opportunities; volunteering; and reassuring people about the safety of family and friends." On Facebook, users can also express preferences and publish status updates. Facebook allows users to connect, facilitating establishing, and preserving relationships [62]. Facebook's Safety Check feature allows users to signal to those in their circle that they are safe or need help [63].

### 3.3. The digital divide: communication gaps

Differences among social and racial-ethnic groups in the use of communication channels, such as social media platforms, could result in both an indirect and direct effect on risk exposure and impact in the context of health outcomes, according to the Structural Influence Model of Communication (SIM) [5]. The model was tested in the context of health communication and health disparities, where it was found that health outcomes were positively correlated with communication inequalities [64,94]. Another study confirmed the theory of the SIM: communication gaps between different social groups, including socioeconomic status, psychological perspectives, geographic factors, and social media use, were found to lead to unequal protection across society during an influenza pandemic [6]. Therefore, it is proposed that existing disparities among vulnerable groups could be exacerbated due to differences in social media access and use [5,6,95].

In disaster situations, the same social groups face similarly heightened risks and vulnerabilities. Given the role of social media platforms as tools for people to share and retrieve information during disaster events, it is imperative to assess the extent of the digital or social media divide among population groups concerning their use of and activity on social media platforms during disasters. Different social groups have different abilities to generate, disseminate, and use information and access, process, and act on it [94]. Differences in population representation across social media platforms have been well-documented in research conducted over the last decade from gender representation [95] and race, ethnicity, and parental educational background [18,65]. Social factors have been found to influence social media platforms [21] and use platform mechanisms differently [22].

Locational factors (urban vs. rural) have also been cited in the discussion of the "digital divide" and disaster resilience disparity. Looking at the difference in social media use patterns across urban and rural settings is important because the challenges in urban areas are different from those in rural places [66]. Rural areas typically lack sufficient human and financial resources compared to their urban counterparts, consequently comprising their resilience [67]. However, at the same time, and perhaps due to the limited resources available, rural places tend to become self-reliant and have stronger intra-community ties and social networks, enhancing resilience [67]. Finally, the impact of disasters is experienced differently in urban and rural settings: while property losses are more significant in urban areas because of the density and value of structures, the relative impact of those losses might be more significant in rural areas [51]. Fatalities and injuries might also be greater in urban areas for some hazards (e.g., heat, earthquakes) but not for others (lightning, flooding) [66].

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

### 3.4. Information checking or seeking

Information seeking or checking is a sense-making process where a person retrieves information that fits his or her point of view [68]. During disasters, people need information that will enable them to make sensible decisions and protective actions that ensure their well-being and safety. Bird et al. [61] and Ryan (2013) [100] explored motivators for social media use during disaster situations during flash flooding events in Australia. The most common reasons for use were to get information on the community's well-being and friends and family, share information, and offer assistance to others [61]. People were further seeking information regarding various infrastructure service disruptions, including road closures and power outages, and work closures [100].

As noted earlier, social media platforms also have use for communicating information, online participation, social capital exchange, and visibility, all of which may be unevenly distributed among different social groups [69]. Education and income were the most significant factors for variation in Internet use among population groups [70]. Hargittai [71] forewarned a 'second-level digital divide' concerning how people use web platforms from the types of activities they conduct, their digital skills, and the opportunities they can access [69]. These activities or behaviors are influenced by one's perception of information reliability and credibility, socioeconomic background [69], social network, and trust [72]. In other fields, literacy, and information-seeking behaviors play substantial roles in health outcome improvements [73]. In their study, it was found that compared with the high-income population, low-income population groups were less likely to turn to healthcare professionals as their first source for health information, and overall, had more difficulty understanding the health information found. Individual, community, and content-level factors each influence a person's sharing and seeking activities. Variations in our social networks lead to different degrees of information salience and review and differences in information uptake and sharing [101,109].

### 3.5. Information sharing and perceived reliability

Information sharing is an action to provide information to other community members who may need it [74,75]. The second-level digital divide discussed by Hagittai [71] helps explain why certain population groups, based on socioeconomic status, are better-informed than others. Some are more socially connected, which influences the extent to which information is available and its quality. There are differences in how, when, and with what information is shared, which help maintain situation awareness inequalities [76,112]. It is proposed that the sharing and checking activities of subgroups of a population vary, reflecting their unique needs during a disaster. Disparities in the information-sharing matter, especially in the context of disasters. As presented by the social media platforms' descriptions, each platform has unique sharing options and ways that users can gather or seek information. In the distribution of information during a disaster, people need the information that will enable them to make sensible decisions about their and their families' well-being and safety.

A key aspect of information finding lies in the reliability of the information. The extent of reliability a person perceives information is dependent on several factors and is related to social factors [110]. These studies did not look into how information distributing behaviors might have differed concerning social contexts and the context of different disaster or hurricane characteristics. It is proposed that information sharing and seeking are unique to different population groups and indicate their specific needs. It would further highlight uniformity in machine learning models using social media data, which assume users have uniform uses.

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

## 4. Methodology

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

### 4.1. Study regions

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

Hurricane Harvey made landfall along the Texas coast in late August 2017 as a category four storm, impacting all 4.7 million inhabitants of Harris County, the most populous county in Houston and Texas. Widespread and devastating flooding caused by record-breaking rainfall made 22 of Houston metro's significant freeways impassable during, and nearly 300,000 households lost power [77].

Hurricane Michael hit the Florida Panhandle and Big Bend region as a Category 5 hurricane. Strong winds and storm surge caused catastrophic damage to buildings, hospitals, and schools [78]. In addition to extensive structural damage, hurricane-force winds caused widespread power outages across the region, where nearly 100% of households across a large portion of the Florida Panhandle lost power, with some of these outages lasting weeks [78]. Inland flooding associated with Hurricane Michael was relatively limited because the storm as the hurricane tracked rapidly across the area [79]. The highest amount of rainfall was observed near Crossroads, GA (Quitman County) at a total of 6.84 inches, with the second-highest amount for the region recorded in Calhoun County, FL, with 6.66 inches [79].

Hurricane Florence made landfall near Wrightsville Beach, N.C. as a Category 1 hurricane, in mid-September 2018. It was the single wettest hurricane on record for the Carolinas and cost $24 billion [80]. It produced extensive wind damage along the North Carolina coast from Cape Lookout, across Cartert, Onslow, Pender, and New Hanover counties. Thousands of downed trees caused widespread power outages to nearly all of eastern North Carolina. The hurricane produced a record-breaking storm surge ranging from 9 to 13 feet and intense rainfall of 20–30 inches, causing life-threatening flooding. The hardest-hit areas included New Bern, Newport, Belhaven, Oriental, North Topsail Beach, Jacksonville, and Downeast Carteret County [80].

### 4.2. Household surveys

Three web-based surveys were developed and distributed to households in the impacted regions via Qualtrics, an online survey panel software company that matches respondent panels with demographic quotas. To represent the vulnerable population groups in each study area, the authors provided quotas created from U.S. Census Bureau data to draw a sample from the study regions based on age, race/ethnicity, income, and health status. All survey participants were required to be 18 years or older who had directly experienced the service disruptions, meaning that these households did not evacuate before the disaster made landfall. Meeting this criterion, 1075 survey respondents were analyzed for Hurricane Harvey, 573 survey respondents were analyzed for Hurricane Florence, and 706 survey respondents were analyzed for Hurricane Michael, combining to a total of 2354 responses. According to power analysis, this is a sufficient sample for conducting inferential statistics that systematically examine associations within the survey data. The purpose of the survey was to collect information on the reliability of social media information and the uses and behaviors of social media users during disaster events concerning geographic characteristics (urban vs. rural), storm severity and characteristics, and population characteristics (race, health condition, income) (Table 1). Having enough demographic diversity in the sample to provide a sound test of the relationships in the correlation analysis is more important than the degree to which sample means and proportions are representative of the study area population [81].

### 4.3. Data

Upon retrieving the data, survey responses were modified into either binary or ordinal indicators for statistical modeling and analysis of the survey results. We adopted eight socioeconomic variables and eight social media variables shown in Table 1, which summarizes all measures and their original and converted values used for our statistical analysis. The vulnerable populations determined the social groups in disasters.

#### 4.3.1. Household sociodemographic factors

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

**Table 1**
Measures used in statistical analysis.

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

(continued on next page)

**Table 1** (*continued*)

| Category | Survey question | Variable name | Survey Response | Data type |
|---|---|---|---|---|
| | [a]Based on the reported county | Urban | Yes<br>No (Rural) | Binary |

[a] Asterisk indicated data retrieved outside of the household empirical surveys.

while preparing for, responding to, and recovering from disaster events [115]. For this analysis and to maintain consistency with the social vulnerability index (SVI), households have been classified into subgroups according to reported ethnic identity, health status, and income level. Age was not used as a factor in the analysis due to the biases introduced by the survey respondents representing households, not individuals. The survey did not differentiate between white Hispanic and non-white Hispanics. Additionally, the 'other' racial category represents households that identified as mixed-race or ethnicity in addition to Pacific Islanders and Native Americans. Pacific Islanders and Native American households were grouped into the Other category because of the low population samples. Most statistical analyses require sample sizes to be greater than or equal to 10. The income group levels were divided into three brackets (low, middle, high), according to recent census data on median household income in Texas [82]. Sub-categories were combined, as shown in Table 1.

#### 4.3.2. Social media use factors

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

### 4.4. Statistical approach

First, univariate statistics of the survey question results were determined and summarized as an absolute frequency concerning each storm event and as a whole (combining all three storm events). Proceeding this step, Welch ANOVA 1-way tests were used to assess the statistically significant differences in household 1) Social Media Use, 2) Social Media Platform Choice, 3) Social Media Information Reliability, and 4) Information Sharing on Social Media across different social and geographic characteristics and storm events, as measured by the eight socioeconomic variables described in Table 1. As the ANOVA test is significant, we also computed Tukey HSD (Tukey Honest Significant Differences) to perform multiple pairwise-comparisons to determine if the mean difference between specific pairs of groups is statistically significant. Results from this analysis component allowed us to formally determine whether or not significant differences in the behaviors and use of social media exist across different population groups. This information informs about whether vulnerable groups are not active on social media during disasters. Some research has used social media data (such as tweets) to determine disparities in social media usage, and their conclusions suggest that because they are not active in social media during disasters based on their metrics, they are at greater risk due to communication gaps [16]. The current analysis could confirm whether the reported results based on social media data are valid.

In the next step, multinomial logistic regression models were used to analyze relationships between social media usage and activity and social characteristics in further depth using the multinom function from the nnet Package in R [83]. The level of the outcomes that we used as our baseline is specified in Table 1. All analyses were performed using R version 3.6, using $\alpha<0.05$ as the statistical significance level. The models tested are shown below, according to the variables summarized in Table 1.

*Model*:

$$\ln\left(\frac{P\left(Y_{n1,2,3}=1\right)}{P(X_n=x)}\right)\sim \text{floodingstatus}_1+\text{weatherforecast}_2+\text{supermarketclosures}_{\ 3}+\text{roadcondition}_{\ 3}+\text{damages}_{\ 3}+\text{servicesstatus}$$

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

## 5. Results & discussion

### 5.1. Survey results

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

### 5.2. Results summary

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

Table 3 summarizes the statistically significant results from the analysis of variance (ANOVA) tests across social and geographic location groups and social media characteristics analyzed. The interpretation of these results is presented below using the results of the Tukey Honest Significant Differences tests. Each cell in the table marked with an "X" signifies a social media characteristic that was determined to have differences when considering different population groups. For an example, Table 3 explains that general social media uptake (S.M Use), Twitter (TW) and Nextdoor (ND) use, and perceived reliability of social media information (Reliability) depends on one's level of educational attainment. Empty cells in the table signify that there is no statistically significant difference in the social media characteristics among different population groups.

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

**Table 3**
Reported disparities among population groups concerning social media characteristics according to ANOVA 1-way tests.

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

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

at all, compared to other racial groups. Facebook is still the most popular and frequently used social media platform (Duggan & Smith, 2013). During Hurricane Harvey, social media users were more likely to be users of multiple platforms than users in Florence and Michael. Interestingly, while statistically significant differences among households of different educational status groups existed, the relationships between education attainment and social media use were not precisely linear. Households with a college degree or higher and households with no degree were more likely than households with a high school diploma to use social media. While this result seems counterintuitive, it is not unfounded in other researchers studying the disparities in social media use across population groups with similar "found patterns" that counter the traditional digital divide [69,114].

Recent studies on social networking sites (SNS) suggest that because of the wide adaption of social media platforms across all population groups, a users' social background is no longer a significant predictor of participation or access to social media [69]. While the difference in whether an individual will use social media or not is not significant, the difference is more likely to be found concerning the information seeking and sharing behaviors and actions, as we confirm in this study's analysis. Social content is more likely to be created by lower-income or racial minorities [118]. Additionally, different social backgrounds trigger different motivations and methods for the use of social media platforms [69]. Found that Teenagers from 'lower-income' families are more enthusiastic about the communication and relational features of these sites while their more elite peers were more interested in the "capital enhancing opportunities" offered by social media platforms and are characterized by limited activity on the platforms to display "a critical stance" [69]

Respondents in the Harvey-impacted region demonstrated a more diverse use of social media platforms. This can indicate a few connections. First, respondents from the Harvey-impacted region were all classified as 'urban-dwellers.' In general research regarding social media users, Urban residents are more likely to be active across other social media platforms, particularly Twitter and Instagram [84]. The broader and more diverse use of social media platforms in the Harvey region is possibly reflective of their urban environment. People residing in urban areas are more likely to be exposed to new technologies and uptake new technologies earlier and quicker than their suburban and rural counterparts. As a result, the broader use may increase the extent of exposure to information surrounding disaster events instead of individuals or households that rely on only one social media platform. Another significant finding was that social media use was less during Michael than both Florence and Harvey. This might be explained by another finding that White households, in general, were less likely than other ethnic and racial groups to be social media users. As other research suggests, social media platforms or social networking sites are more likely to be used by individuals from less-advantaged socioeconomic or cultural backgrounds [69].

### *5.3. Geographic and urban-rural disparities in social media and platform uptake*

Using an analysis of variance (ANOVA), urban and rural geographic factors were not found to have statistically significant effects on the use of social media during the hurricane events in ($F$ (df = 1, N = 2354) = 0.487, $p = 0.485$). However, statistically, significant differences were observed concerning urban and rural households and the type of platforms used by households (Table 3). A posthoc Tukey test showed that households in urban areas were more likely to be active on Twitter and Nextdoor than their rural counterparts ($M = 0.123 \pm 0.034$, $p < 0.001$; $M = 0.095 \pm 0.187$, $p < 0.001$). Similarly, Facebook was not as prominent as a social media platform choice in urban areas ($M = -0.042 \pm -0.120$, $p < 0.001$). The extent of social media use was different across households according to the storm event classification ($F$ (2,2351) = 3.951, $p = 0.019$). Using the posthoc test there were fewer social media users among households impacted by Hurricane Michael compared to both Harvey ($M = -0.103 \pm 0.005$, $p = 0.075$) and Florence ($M = -0.133 \pm 0.009$, $p = 0.021$). The difference between social media users among households impacted by Harvey and Florence was not statistically significant ($p = 0.660$). Similarly, statistically significant differences were found regarding the platform used (Table 4a, Appendix). The amount of Twitter users was statistically significant and greater among households impacted by Harvey than Florence ($M = 0.010 \pm 0.113$ $p = 0.016$), which may indicate the fact that Harvey-impacted areas were all classified as urban. Nextdoor found less use in the Michael-impacted areas compared to that of both Florence and Harvey ($M = -0.149 \pm -0.030$, $p < 0.001$; ($M = -0.174 \pm -0.070$, $p < 0.001$).

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

### 5.4. Sociodemographic disparities in social media and platform uptake

Some studies have identified a 'reproduction' of social inequalities and ethnic divisions in the patterns of social media platform adoption displayed by teenagers and young people: the specific social media platforms on which youth choose to create a profile tends to reflect their social class and ethnic background [69]. Sociodemographic variables (parental education, socioeconomic status, and ethnicity) do not explain young people's general use (or non-use) of social media platforms. Rather, they are associated with the particular SNSs they embrace [18]. One social media platform's choice over another is influenced by a mechanism of distinction that reproduces class and ethnic differences. Below are the statistical results from our study which support existing literature on social class disparities in social media platform use and uptake.

### 5.5. Educational attainment

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

### 5.6. Racial and ethnic groups

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

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

### 5.7. Income level

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

### 5.8. Health status

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

### 5.9. Differences in information-seeking activity

#### 5.9.1. Disparities across storm events

Logistic and general regression models were employed to test for significant relationships between social media information-seeking activity and storm and sociodemographic characteristics. Tables 6–8 of the Appendix section summarize the estimate coefficients, standard error, odds ratio, and p-value of significance for each indicator and its predictors. Different ethnic groups reported different use-applications for social media during the storms. In general, minorities were less likely to report using social media for information about *Damages* and the *Status of Service Disruptions* during Michael and Florence. Variations in usages by the population became more evident when narrowing down to the choice of platform used by households and using social media during the storms. Racial minorities expressed interest in finding information on supermarket closings on social media. On Nextdoor, there was a positive correlation between the use of the app and searching for supermarket closings. However, racial minorities were less likely to be users of this platform. Social media users during both Harvey and Florence were most concerned about finding information regarding road conditions and flooding status, while those impacted by Michael were more likely to use social media to check the on-road status and physical damages (Fig. 1). This finding indicates an association between storm characteristics and information seeking. From this finding, we can infer the critical characteristics of Hurricane Michael. Given that there was minor inland flooding caused by the hurricane, it makes sense that impacted households did not highly demand information on flooding. Regression models were used to determine the nature of (negative or positive) the relationships between the specific storm impact attributes (information seeking purpose) and the storms themselves (Table 9). The results show that for Michael, households were concerned most with storm damage

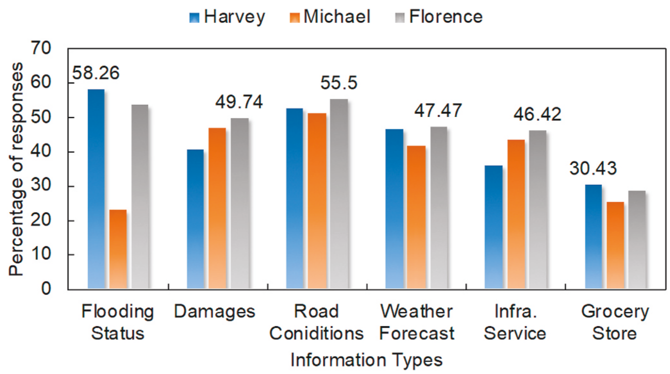


**Fig. 1.** Information types checked on social media during storms (%).

**Table 9**
Information checked during storms.

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

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

### 5.9.2. *Differences across social media platforms*

The relationship between social media platforms and information sought was also explored to determine whether there is a statistically significant difference in platforms' usage purposes. This information can also inform us about the types of information about a disaster present on one social media platform and not another and demonstrates the purpose of the use and role that platforms have during disasters. Certain population groups are more likely than others to use specific platforms than others, therefore it is important to look at the difference in information seeking activity across platforms. It was found that for households using Facebook, Weather, Damages, and Service Status were most often checked (Table 10). For Twitter, only checking for Weather updates was statistically significant ($\beta = 0.065$, p = 0.047). For Nextdoor Users, Supermarket, Service status, and road closures were positively correlated to the use of Nextdoor (Table 10). However, only supermarket status was statistically significant ($\beta = 0.068$, p = 0.041).

Prior studies indicate that different racial/ethnic populations display varying internet and social media use trends over time. The use of social networking applications increased across all ethnicities, where English-speaking Latino and African American internet users were on social media platforms at higher rates than White users between 2010 and 2013 [87]. Since 2013, English-speaking Latinos' use of social networking websites has been statistically significantly higher than other races [88]. Among Internet users, racial and ethnic minorities regularly access these platforms at higher rates than Whites [108].

**Table 10**
Social media platform and information seeking activity.

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

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

### 5.10. Disparities in perceived reliability of information on social media

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

These findings have significant underlying implications related to the social connectivity and network of households. According to other studies, the judgment of misinformation and or information reliability narrows down to the level of trust an individual has with the information sharer [89]. This study demonstrates that who shares an article on a social media site like Facebook has an even more significant influence on whether people trust what they see. A trusted sharer has more significant effects on beliefs about the news than a reputable media source [89]. Furthermore, education plays a crucial role in the perception of information from social media. Viswanath (2006) [94] published insightful research on the differential use of social media and information sharing across social groups concerning health information and its correlation to health outcomes in different population groups. Individual characteristics, particularly education status, have a substantial impact on one's ability or capacity to process and act on information; it provides the necessary confidence, sense of efficacy, and knowledge in enabling someone to navigate complex systems, like disasters [94]. This is an important finding because machine learning algorithms generally assume uniform usage and social media users' behavior.

News consumers often see news filtered through others who share the content rather than directly to the reporting source [69]. This leads to concerns about misinformation infiltrating these networks and spreading across the public sphere. Given the less structured and more participatory information environment, what can we say about people's trust in the news on social media: people are more likely to trust an article on social media if it is shared by a public figure they trust than by one they do not trust [89]. They are also more likely with a trusted public figure sharing news to say they would engage with the article in ways like sharing it or recommending the source to friends or family [89]. If people do not know a source, they approach its information similar to how they would become sources they know and trust [89]. People's trust in the news they see on social media is strongly related to who shares it.

### 5.11. Disparities in information-sharing across sociodemographic and geographic characteristics

Information sharing through social media was found to be different across the storm events ($F (2, 1542) = 6.334$, $p = 0.002$). Information sharing through social media was more prominent during Hurricane Harvey compared to both Michael ($M = -0.143 \pm -0.008$, $p = 0.023$) and Florence ($M = 0.025 \pm 0.164$, $p = 0.004$)). Similarly, information sharing was statistically significantly higher in urban areas compared to rural areas ($F (1,1542) = 10.12$, $p = 0.001$); ($M = 0.037 \pm 0.158$, $p = 0.002$), Chronic Health problems ($F (1,1543) = 3.197$, $p = 0.074$). No statistically significant differences were found among racial groups ($p = 0.226$), income ($p = 0.841$), mobility health issue groups ($p = 0.143$), or education attainment groups ($p = 0.41$). However, ANOVA tests were conducted to assess group difference while controlling for each storm event. The results illustrate a different narrative. During Hurricane Florence, disparities in information sharing were found among racial and ethnic groups ($F (4,392) = 3.224$, $p = 0.013$). During Hurricane Florence, households identifying as both Other and White reported more information sharing activity compared to Black and African American households ($M = -0.007 \pm 0.357$, $M = 0.0.046 \pm 0.630$, $p = 0.014$). No statistically significant differences were found across other racial and ethnic groups during Florence or Harvey ($F (4,704) = 1.709$, $p = 0.146$); ($F (4, 434) = 0.700$, $p = 0.592$). During both Hurricane Harvey and Michael, households with chronic health patients were more likely to share information on social media compared to households without a chronic health member ($F (1, 437) = 3.042$, $p = 0.082$); $M = -0.011 \pm 0.180$; $p = 0.082$).; member ($F (1, 707) = 2.881$, $p = 0.090$); $-0.009$ $0.134$; $0.090$). No statistically significant differences were found among income groups ($F (5, 153) = 0.411$; $p = 0.840$), education ($F (2, 1542) = 0.893$, $p = 0.410$), mobility ($F (1, 1543) = 2.148$, $p = 0.134$).

Information sharing through social media was more prominent during Hurricane Harvey compared to both Michael and Florence. It is not possible to conclude whether this is due to more extensive damages or impact from the survey information. Other possible explanations can be related to the communication network disruptions, connectivity, and strength of households' social ties, which was not included in this analysis. In general, there were no significant variations in information sharing among different population groups. However, White and Other racial and ethnic households were statistically more likely to have shared information compared to Other racial or ethnic groups in Hurricane Florence. During Hurricane Harvey, Black households were found to share more information than other groups; however, the difference was not statistically significant. During Harvey and Michael, households with chronic health patients were more likely to share information on social media compared to households without a chronic health member. This is a significant finding as it contradicts studies using digital trace data from social media, which have found certain population groups in communities to be underrepresented during disasters [16]. Furthermore, this can indicate that they had a greater need for information (about healthcare facilities, etc.) and utilized social media for information seeking. Examples of using social media platforms for emergency help were well-documented during Hurricane Harvey. This is a significant bias to address in future work using social media data to analyze different disaster phenomena.

As noted, different platforms have different features that influence the type and format of information shared. While studying disaster impact disparities, the concern is regarding communication and/or knowledge gaps that exist in communities due to gaps in social media use and platform. Another significant phenomenon of social media assessed in this study was the act of information sharing; vulnerable population groups were less likely to report using social media to share information, except for households with chronically ill household members. On the other side, it is apparent that households used social media as passive users, meaning that they used the platforms to collect information about the storm instead of sharing information. Understanding the usage of social media and the platforms used by households to gather and share information during disasters helps identify the population needs, the most efficient platforms for sharing information, and ensuring it is dispersed to the right audience. With respect to machine learning algorithms and techniques for disaster informatics, the results highlight discrepancies in the outcomes of these models. Blank (2013) [118] observed that sharing 'social and entertainment content' online is influenced by income, but with an inverse pattern to what we might expect: users with higher incomes produce less content online [69]. Education is only moderately associated with the use of SNSs; those without high school education are more likely to use SNSs than high school graduates [111]. A nationwide survey in the U.S. showed that individuals of lower socioeconomic status are more frequent users of Facebook than those of higher status [102]. Teenagers whose parents hold a high school diploma are more likely to use SNSs than those with college-educated parents [119].

This information can give insight into the needs and priorities of different population groups during a disaster. Prior studies indicate that different racial and ethnic populations display varying internet and social media use trends over time. Moreover, between 2010 and 2013, the use of social networking websites increased across all races, with English-speaking Latino and African American Internet users accessing social media platforms at higher rates than White users. Since 2013, English-speaking Latinos' use of social networking websites has been statistically significantly higher than that of other races [87]. While the gap access to the internet is quickly closing, the use purposes and internet literacy remain a source of social division [108].

## 6. Conclusion

This paper explored the relationship between population groups and their behavioral patterns related to using social media during disasters. The analysis in this study is conducted in the context of three primary disaster events, Hurricane Harvey, Florence, and Michael. A robust empirical understanding of social media users' characteristics and their activity on social media platforms during disaster events is essential for addressing the digital divide and equitable resilience. Social media is becoming a key platform for information dispersion during disasters; therefore, any disparities or gaps in the use can lead to gaps in communication and understanding of disaster impacts. From the exploratory analysis presented in this paper, it is clear that social and location factors play significant roles in the uptake of social media platforms and the determinants of information seeking and information sharing during disasters. Results from this analysis confirm the following: (1) Socioeconomic factors along with location and regional effects play a role in determining not only platform uptake but both motivations for information seeking and the action of information sharing on social media, (2) The type of social media platform influences the type of information people seek, (3) Households from lower socioeconomic and minority backgrounds were more likely to use social media platforms to sought out different information on social media than their peer, (4) perceptions of information reliability are also influenced by social divides, where households in rural areas, lower-income groups, and racial minorities were more likely to report greater unreliability in social media information. These findings provide a deeper empirical understanding regarding social media usage and differences among various sub-populations for information seeking and sharing during disasters.

This study's findings provide important insights for practice related to information communication in disaster management and intend to inform advanced data mining methods of social media data. First, this study identifies the geographic and population disparities of using social media, which may lead to unequal information access and situation awareness. This signifies that different people have various levels of capabilities to resistant the negative impacts of disasters. Existing disaster management does not consider such disparities and may cause unequal resource allocation and relief supports. Second, different people require different types of information by using social media. Based on such understanding, social media platforms can distribute different information to different groups of people to enhance their accessibility of certain types of information. First responders and relief organizations can also use social media platforms to share the information needed by people to enhance their situational awareness in disasters. As discussed in the literature review and introduction, the increasing use and reliance on data from social media platforms in data mining and machine learning models require techniques that are "discrimination-aware" [90].

From the presented analysis, we have uncovered several key disparities related to sociodemographic and geographic factors in the social media users, their purpose for using social media during disasters, and perception of information shared across the platforms. Therefore, the empirical findings of this study can guide the development of algorithmic models that consider such biases. For example, developers may opt for specific pre-processing methods that omit possible bias to prevent the new model from learning discriminatory behaviors [90]. Furthermore, in developing models and data mining, there is a need to "keep the human in the loop." Humans have a critical role in providing insight, guided by empirical research, for improving fairness in model outcomes [90].

## Declaration of competing interest

The authors declare that there are no known conflicts of interest associated with this publication.

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## Appendix

**Table 2**
Percent of social media users from total households across hurricane events

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

**Table 4a**
Difference in Social Media Platform according to Geographic Factors

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

**R = residual error.

**Table 5a**
Income, Education, and Health(Mobility) ANOVA-1 Results

| | Social Media Platform Group | Df | Sum Sq | Mean Sq | F value | Pr (>F) |
|---|---|---|---|---|---|---|
| HEALTH: Mobility | Nextdoor | 2 | 0.01 | 0.01437 | 0.106 | 0.745 |
| | | ***R:***1551 | ***R:***200.0 | ***R:***0.1290 | | |
| | Twitter | 2 | 3.23 | 0.8076 | 6.501 | 3.46e-05 |
| | | ***R:***1554 | ***R:***192.79 | ***R:***0.124 | | |
| | Facebook | 2 | 2.16 | 0.4320 | 4.489 | 0.001 |
| | | ***R:*** 1543 | ***R:*** 149.32 | ***R:*** 0.0968 | | |
| EDUCATION | Nextdoor | 2 | 2.76 | 1.381 | 10.30 | 0.000 |
| | | ***R:***1542 | ***R:***206.78 | ***R:***0.134 | | |
| | Twitter | 2 | 0.604 | 0.302 | 2.397 | 0.0913 |
| | | ***R:***1542 | ***R:***194.40 | ***R:***0.1261 | | |
| | Facebook | 2 | 0.040 | 0.022 | 0.231 | 0.794 |
| | | ***R:***1542 | ***R:***149.69 | ***R:***0.097 | | |
| INCOME | Nextdoor | 5 | 10.5 | 2.099 | 16.28 | 1.12e-15 |
| | | ***R:***1551 | ***R:***200.0 | ***R:***0.129 | | |
| | Twitter | 5 | 0.640 | 0.127 | 1.001 | 0.411 |
| | | ***R:***1539 | ***R:***194.42 | ***R:***0.126 | | |
| | Facebook | 5 | 2.16 | 0.4320 | 4.527 | 0.000 |
| | | ***R:***1539 | ***R:***147.56 | ***R:***0.096 | | |

**R = residual error.

**Table 11a**
Disparities in Information Reliability on Social Media, ANOVA-1 Way Test

| | Reliability Group | Df | Sum Sq | Mean Sq | F value | Pr (>F) |
|---|---|---|---|---|---|---|
| RACE& ETHNICITY | *Not at all* | 4 | 0.072 | 0.018 | 1.407 | 0.229 |
| | | 1540 | 19.669 | 0.013 | | |
| | *Somewhat unreliable* | 4 | 0.690 | 0.172 | 2.43 | 0.046 |
| | | ***R:*** 1540 | ***R:***109.15 | ***R:***0.071 | | |
| | *Neutral* | 4 | 2.84 | 0.711 | 5.099 | 0.000 |
| | | 154 | 214.73 | 0.139 | | |
| | *Somewhat reliable* | 4 | 12.5 | 3.121 | 13.150 | 1.56e-10 |
| | | ***R:***1540 | ***R:***365.6 | ***R:***0.237 | | |
| | *Very Reliable* | 4 | 2.86 | 0.716 | 3.525 | 0.007 |
| | | ***R:***1540 | ***R:***312.69 | ***R:***0.203 | | |
| *EDUCATION* | *Not at all* | 2 | 0.193 | 0.097 | 7.629 | 0.001 |
| | | ***R:***1542 | ***R:***19.548 | ***R:***0.013 | | |
| | *Somewhat unreliable* | 2 | 0.11 | 0.053 | 0.746 | 0.475 |
| | | ***R:***154 | ***R:***109.73 | ***R:***0.071 | | |
| | *Neutral* | 2 | 1.11 | 0.554 | 3.948 | 0.020 |
| | | ***R:***1542 | ***R:***216.46 | ***R:***0.140 | | |
| | *Somewhat reliable* | 5 | 5.30 | 1.060 | 4.375 | 0.001 |
| | | ***R:***1539 | ***R:***372.8 | ***R:***0.242 | | |
| | *Very Reliable* | 2 | 2.11 | 1.054 | 5.184 | 0.006 |
| | | ***R:***1542 | ***R:***313.44 | ***R:***0.20 | | |
| *INCOME* | *Not at all* | 5 | 0.089 | 0.018 | 1.396 | 0.223 |
| | | 1539 | 19.652 | 0.013 | | |
| | *Somewhat unreliable* | 5 | 0.36 | 0.071 | 1.004 | 0.414 |
| | | ***R:***153 | ***R:***109.48 | ***R:***0.071 | | |
| | *Neutral* | 5 | 0.6 | 0.121 | 0.858 | 0.509 |
| | | ***R:***1539 | ***R:***217.0 | ***R:***0.141 | | |
| | *Somewhat reliable* | 5 | 5.3 | 1.060 | 4.375 | 0.001 |
| | | ***R:***1539 | ***R:***372.8 | ***R:***0.242 | | |
| | *Very Reliable* | 5 | 0.39 | 0.080 | 0.382 | 0.861 |
| | | ***R:***1539 | ***R:***315.16 | ***R:***0.205 | | |

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

**Table 6**
Information seeking activity during storms by racial and ethnic group; *Hurricane Harvey*

| | Info Checked | Estimate | Std. Error | Wald | Sig. | OR |
|---|---|---|---|---|---|---|
| Asian | Intercept | −3.400 | 0.740 | −4.590 | <0.001 | 0.033 |
| | Flooding Status | −1.160 | 1.150 | −1.010 | 0.313 | 0.314 |
| | Weather | 0.165 | 0.469 | 0.353 | 0.724 | 1.180 |
| | Supermarket | −1.130 | 0.494 | −2.280 | 0.023 | 0.324 |
| | Road Condition | 0.526 | 0.611 | 0.860 | 0.390 | 1.692 |
| | Damages | 0.894 | 0.470 | 1.900 | 0.057 | 2.444 |
| | Service Status | 1.040 | 1.300 | 0.799 | 0.424 | 2.833 |
| Black and African American | Intercept | 0.717 | 0.661 | 1.080 | 0.278 | 2.048 |
| | Flooding Status | 0.126 | 0.220 | 0.572 | 0.567 | 1.134 |
| | Weather | 0.145 | 0.213 | 0.680 | 0.496 | 1.156 |
| | Supermarket | −0.378 | 0.260 | −1.450 | 0.147 | 0.685 |
| | Road Condition | 0.285 | 0.210 | 1.360 | 0.175 | 1.330 |
| | Damages | −0.745 | 0.726 | −1.030 | 0.305 | 0.475 |
| | Service Status | −1.610 | 0.402 | −4.020 | 0.000 | 0.199 |
| Latino and Hispanic | Intercept | 1.490 | 1.060 | 1.400 | 0.160 | 4.419 |
| | Flooding Status | 0.169 | 0.274 | 0.618 | 0.536 | 1.184 |
| | Weather | 0.420 | 0.262 | 1.600 | 0.110 | 1.522 |
| | Supermarket | −0.356 | 0.327 | −1.090 | 0.277 | 0.700 |
| | Road Condition | 0.134 | 0.258 | 0.519 | 0.604 | 1.143 |
| | Damages | −1.510 | 1.130 | −1.340 | 0.181 | 0.221 |
| | Service Status | −3.920 | 1.040 | −3.770 | <0.001 | 0.020 |
| Other | Intercept | 0.612 | 1.090 | 0.563 | 0.574 | 1.844 |
| | Flooding Status | 0.052 | 0.394 | 0.131 | 0.896 | 1.053 |
| | Weather | 0.474 | 0.365 | 1.300 | 0.194 | 1.606 |
| | Supermarket | −0.538 | 0.463 | −1.160 | 0.245 | 0.584 |
| | Road Condition | 0.684 | 0.401 | 1.700 | 0.089 | 1.981 |
| | Damages | 0.756 | 1.490 | 0.506 | 0.613 | 2.131 |
| | Service Status | −3.400 | 0.740 | −4.590 | <0.001 | 0.033 |

*OR = Odds Ratio.

**Table 7**
Information seeking activity during storms by racial and ethnic group; *Hurricane Michael*

| | Info Checked | Estimate | Std. Error | Wald | Sig. | OR |
|---|---|---|---|---|---|---|
| Asian | Intercept | −16.000 | 0.652 | −24.500 | <0.001 | <0.001 |
| | Flooding Status | 0.884 | 1.52 | 0.580 | 0.562 | 2.420 |
| | Weather | 0.884 | 1.520 | 0.580 | 0.562 | 2.420 |
| | Supermarket | −1.690 | 1.360 | −1.250 | 0.213 | 0.185 |
| | Road Condition | 0.181 | 1.400 | 0.126 | 0.900 | 1.200 |
| | Damages | 13.400 | 0.652 | 0.200 | <0.001 | $6.89 \times 10^8$ |
| | Service Status | −1.170 | 1.610 | −0.726 | 0.468 | 0.311 |
| Black and African American | Intercept | −0.482 | 1.300 | −0.369 | 0.712 | 0.610 |
| | Flooding Status | −1.170 | 1.610 | −0.726 | 0.468 | 0.311 |
| | Weather | −0.434 | 0.357 | −1.220 | 0.224 | 0.648 |
| | Supermarket | 1.040 | 0.278 | 3.750 | <0.001 | 2.830 |
| | Road Condition | −0.752 | 0.271 | −2.770 | 0.006 | 0.471 |
| | Damages | −0.327 | 0.266 | −1.230 | 0.219 | 0.721 |
| | Service Status | 0.801 | 0.266 | 3.010 | 0.003 | 2.230 |
| Latino and Hispanic | Intercept | −0.752 | 0.271 | −2.770 | 0.006 | 0.471 |
| | Flooding Status | −0.052 | 0.295 | −0.174 | 0.862 | 0.950 |
| | Weather | −0.707 | 0.365 | −1.940 | 0.053 | 0.493 |
| | Supermarket | −3.130 | 1.180 | −2.660 | 0.008 | 0.044 |
| | Road Condition | 0.947 | 0.806 | 1.180 | 0.240 | 2.580 |
| | Damages | −0.779 | 0.732 | −1.060 | 0.287 | 0.459 |
| | Service Status | 1.270 | 0.838 | 1.510 | 0.130 | 3.560 |
| Other | Intercept | 1.320 | 1.090 | 1.210 | 0.226 | 3.760 |
| | Flooding Status | −1.510 | 0.757 | −1.990 | 0.047 | 0.222 |
| | Weather | −1.120 | 1.090 | −1.020 | 0.305 | 0.326 |
| | Supermarket | −1.990 | 0.665 | −3.000 | 0.003 | 0.136 |
| | Road Condition | 0.274 | 0.537 | 0.511 | 0.609 | 1.320 |
| | Damages | 0.060 | 0.504 | 0.119 | 0.905 | 1.060 |
| | Service Status | −0.088 | 0.518 | −0.170 | 0.865 | 0.916 |

*OR = Odds Ratio.

**Table 8**
Information seeking activity during storms by racial and ethnic group; *Hurricane Florence*

| | Info Checked | Estimate | Std. Error | Wald | Sig. | OR |
|---|---|---|---|---|---|---|
| Asian | Intercept | −2.390 | 1.260 | −1.900 | 0.058 | 0.092 |
| | Flooding Status | 12.200 | 0.674 | 18.100 | <0.001 | $2.02 \times 10^8$ |
| | Weather | 0.117 | 1.460 | 0.080 | 0.936 | 1.120 |
| | Supermarket | 14.900 | 0.674 | 22.100 | <0.001 | $3.02 \times 10^8$ |
| | Road Condition | −0.675 | 2.010 | −0.335 | 0.737 | 0.509 |
| | Damages | −19.000 | <0.001 | $-3.56 \times 10^8$ | <0.001 | <0.001 |
| | Service Status | −26.900 | 0.674 | −40.000 | <0.001 | <0.001 |
| Black and African American | Intercept | −0.728 | 0.474 | −1.540 | 0.124 | 0.483 |
| | Flooding Status | 0.424 | 0.456 | 0.931 | 0.352 | 1.530 |
| | Weather | −0.005 | 0.321 | −0.017 | 0.987 | 0.995 |
| | Supermarket | 0.920 | 0.322 | 2.850 | 0.004 | 2.510 |
| | Road Condition | −0.950 | 0.407 | −2.340 | 0.019 | 0.387 |
| | Damages | −0.277 | 0.331 | −0.835 | 0.404 | 0.758 |
| | Service Status | −0.607 | 0.626 | −0.970 | 0.332 | 0.545 |
| Latino and Hispanic | Intercept | −2.290 | 0.818 | −2.800 | 0.005 | 0.101 |
| | Flooding Status | −0.600 | 0.583 | −1.030 | 0.304 | 0.549 |
| | Weather | 0.218 | 0.499 | 0.437 | 0.662 | 1.240 |
| | Supermarket | −0.003 | 0.482 | −0.005 | 0.996 | 0.997 |
| | Road Condition | 0.248 | 0.659 | 0.377 | 0.706 | 1.280 |
| | Damages | −0.720 | 0.489 | −1.470 | 0.141 | 0.487 |
| | Service Status | 0.365 | 0.926 | 0.395 | 0.693 | 1.440 |
| Other | Intercept | −1.680 | 0.613 | −2.740 | 0.006 | 0.186 |
| | Flooding Status | 0.191 | 0.680 | 0.280 | 0.779 | 1.210 |
| | Weather | 1.210 | 0.530 | 2.270 | 0.023 | 3.340 |
| | Supermarket | −0.446 | 0.466 | −0.958 | 0.338 | 0.640 |
| | Road Condition | −0.557 | 0.541 | −1.030 | 0.303 | 0.573 |
| | Damages | −0.251 | 0.461 | −0.544 | 0.586 | 0.778 |
| | Service Status | −0.973 | 0.792 | −1.230 | 0.219 | 0.378 |

*OR = Odds Ratio.

## References

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

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

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

[4] J.S. Becker, D. Paton, D.M. Johnston, K.R. Ronan, J. McClure, The role of prior experience in informing and motivating earthquake preparedness, Int. J. Disas. Risk Reduct. 22 (2017) 179–193, https://doi.org/10.1016/j.ijdrr.2017.03.006.
[5] K. Viswanath, M.W. Kreuter, Health disparities, communication inequalities, and eHealth, Am. J. Prev. Med. 32 (5 Suppl) (2007) S131–S133, https://doi.org/10.1016/j.amepre.2007.02.012.
[6] E. Vaughan, T. Tinker, Effective health risk communication about pandemic influenza for vulnerable populations, Am. J. Publ. Health 99 (S2) (2009) S324–S332, https://doi.org/10.2105/ajph.2009.162537.
[7] J. Earl, CITASA: intellectual past and future, Inf. Commun. Soc. 18 (5) (2015) 478–491, https://doi.org/10.1080/1369118X.2015.1008544.
[8] M. Mendoza, B. Poblete, C. Castillo, Twitter under Crisis: Can We Trust what We RT? 1st Workshop on Social Media Analytics (SOMA '10), 2010. Retrieved from http://snap.stanford.edu/soma2010/papers/soma2010_11.pdf.
[9] H. Gao, G. Barbier, R. Goolsby, Harnessing the crowdsourcing power of social media for disaster relief, IEEE Intell. Syst. 26 (3) (2011) 10–14, https://doi.org/10.1109/MIS.2011.52.
[10] X. Guan, C. Chen, Using social media data to understand and assess disasters, Nat. Hazards 74 (2) (2014) 13, https://doi.org/10.1007/s11069-014-1217-1.
[11] S. Nagar, A. Seth, A. Joshi, Characterization of Social Media Response to Natural Disasters, 2012. WWW 2012 – SWDM'12 Workshop. Retrieved from http://delivery.acm.org/10.1145/2190000/2188177/p671-nagar.pdf?ip=165.91.13.122&id=2188177&acc=ACTIVE%20SERVICE&key=B63ACEF81C6334F5%2E79B51EFA2DE92FE8%2E4D4702B0C3E38B35%2E4D4702B0C3E38B35&__acm__=1576699347_328fd1c5881b01234182ddad624f8c46.
[12] C. Reuter, A.L. Hughes, M.-A. Kaufhold, Social media in crisis management: an evaluation and analysis of crisis informatics research, Int. J. Hum. Comput. Interact. 34 (4) (2019) 280–294, https://doi.org/10.1080/10447318.2018.1427832.
[13] Y. Xiao, Q. Huange, K. Wu, Understanding social media data for disaster management, Nat. Hazards 79 (2015) 16, https://doi.org/10.1007/s11069-015-1918-0.
[14] F. Chao, F. Wu, A. Mostafavi, A Hybrid Machine Learning Pipeline for Automated Mapping of Events and Locations from Social Media in Disasters, IEEE Access, 2020.
[15] C. Zhang, C. Fan, W. Yao, X. Hu, A. Mostafavi, Social media for intelligent public information and warning in disasters: an interdisciplinary review, Int. J. Inf. Manag. 49 (2019) 190–207, https://doi.org/10.1016/j.ijinfomgt.2019.04.004.
[16] R. Samuels, J.E. Taylor, Applied methodology for identifying hurricane-induced social media signal changes in vulnerable populations, in: ASCE Computing in Civil Engineering 2019, 2019.
[17] Z. Wang, N.S.N. Lam, N. Obradovich, X. Ye, Are vulnerable communities digitally left behind in social responses to natural disasters? An evidence from Hurricane Sandy with Twitter data, Appl. Geogr. 108 (2019) 1–8, https://doi.org/10.1016/j.apgeog.2019.05.001.
[18] E. Hargittai, Whose space? Differences among users and non-users of social network sites, J. Computer-Mediated Commun. 13 (1) (2007) 276–297, https://doi.org/10.1111/j.1083-6101.2007.00396.x.
[19] Y. Jiang, Z. Li, X. Ye, Understanding demographic and socioeconomic biases of geotagged twitter users at the county level, Cartogr. Geogr. Inf. Sci. 46 (3) (2019) 228–242.
[20] M.M. Malik, H. Lamba, C. Nakos, J. Pfeffer, Population bias in geotagged tweets, in: Ninth International AAAI Conference on Web and Social Media, 2015, April.
[21] A. Mislove, S. Lehmann, Y.Y. Ahn, J.P. Onnela, J.N. Rosenquist, Understanding the demographics of Twitter users, in: Fifth International AAAI Conference on Weblogs and Social Media, 2011, July.
[22] A. Olteanu, C. Castillo, F. Diaz, E. Kiciman, Social data: biases, methodological pitfalls, and ethical boundaries, Front. Big Data 2 (2019) 13, https://doi.org/10.3389/fdata.2019.00013.
[23] R. Cohen, D. Ruths, Classifying Political Orientation on Twitter: It's Not Easy! International AAAI Conference on Weblogs and Social Media, 2013.
[24] M.F. Goodchild, J.A. Glennon, Crowdsourcing geographic information for disaster response: a research frontier, Int. J. Digital Earth 3 (3) (2010) 231–241, https://doi.org/10.1080/17538941003759255.
[25] M.F. Goodchild, L. Li, Assuring the quality of volunteered geographic information, Spat. Statis. 1 (2012) 110–120, https://doi.org/10.1016/j.spasta.2012.03.00.
[26] W.Y.S. Chou, Y.M. Hunt, E.B. Beckjord, R.P. Moser, B.W. Hesse, Social media use in the United States: implications for health communication, J. Med. Internet Res. 11 (4) (2009) e48, https://doi.org/10.2196/jmir.1249.
[27] S.R. Hiltz, A.L. Hughes, M. Imran, L. Plotnick, R. Power, M. Turoff, Exploring the usefulness and feasibility of software requirements for social media use in emergency management, Int. J. Disas. Risk Reduct. 42 (2020) 101367, https://doi.org/10.1016/j.ijdrr.2019.101367.
[28] R.L. Briones, B. Kuch, B.F. Liu, Y. Jin, Keeping up with the digital age: how the American Red Cross uses social media to build relationships, Publ. Relat. Rev. 37 (1) (2011) 37–43, https://doi.org/10.1016/j.pubrev.2010.12.006.
[29] K. Eismann, O. Posegga, K. Fischbach, COLLECTIVE BEHAVIOUR, SOCIAL MEDIA, AND DISASTERS: A SYSTEMATIC LITERATURE REVIEW, in: ECIS 2016 Proceedings, 104. Retrieved from, Association for Information Systems, 2016 http://aisel.aisnet.org/ecis2016_rp/104.
[30] D. Ruths, J. Pfeffer, Social media for large studies of behavior, Science 346 (6213) (2014) 1063, https://doi.org/10.1126/science.346.6213.1063.
[31] Z. Tufekci, Big Questions for Social Media Big Data: Representativeness, Validity and Other Methodological Pitfalls, 2014.
[32] J.B. Houston, M.L. Spialek, J. Cox, et al., The centrality of media and communication in fostering community resilience: a framework for assessment and intervention, Am. Behav. Sci. 59 (2015) 270–283, https://doi.org/10.1177/0002764214548563.
[33] S. Nicholls, The resilient community and communication practice, Aust. J. Emerg. Manag. 27 (2012) 46–51.
[34] R.L. Pfefferbaum, R. Klomp, Community resilience, disasters, and the public's health, in: F.G. Murphy (Ed.), Community Engagement, Organization and Development for Public Health Practice, Springer, New York, 2013, pp. 275–298.
[35] H. Rodriguez, W. Diaz, J. Santos, B.E. Aguirre, Communicating risk and uncertainty: science, technology, and disasters at the crossroads, in: Handbook of Disaster Research, Springer, New York, 2007, pp. 476–488.
[36] Nadine Sarter, David Woods, Situation awareness: a critical but ill-defined phenomenon, Int. J. Aviat. Psychol. 1 (1991), https://doi.org/10.1207/s15327108ijap0101_4.
[37] C. Chen, P. Ractham, L. Kaewkitipong, The community-based model of using social media to share knowledge to combat crises, PACIS 2014 Proceed. 387 (2014) 2014, https://jcom.sissa.it/archive/13/04/JCOM_1304_2014_R01.
[38] M.E. Keim, E. Noji, Emergent use of social media: a new age of opportunity for disaster resilience, Am J Disaster Med 6 (1) (2011 Jan-Feb) 47–54. PMID: 21466029.
[39] L. Palen, S.B. Liu, Citizen communications in crisis: anticipating a future of ICT-supported public participation, in: CHI 2007 Proceedings • Emergency Action, 2007. Retrieved from http://www.hcitang.org/uploads/Teaching/palenliu-chi07.pdf.
[40] J. Kim, MMei Hastak, Social network analysis: characteristics of online social networks after a disaster, Int. J. Inf. Manag. 38 (2018) 86–96, https://doi.org/10.1016/j.ijinfomgt.2017.08.003.
[41] F. Shaw, J. Burgess, K. Crawford, A. Bruns, Sharing news, making sense, saying thanks: patterns of talk on Twitter during the Queensland Floods, Aust. J. Commun. 40 (1) (2013) 23–39.
[42] S. Vieweg, A.L. Hughes, K. Starbird, L. Palen, Microblogging during Two Natural Hazards Events: what Twitter May Contribute to Situational Awareness, 2010. CHI 2010. Retrieved from https://cmci.colorado.edu/~palen/vieweg_1700_chi2010.pdf.
[43] H. Carter, J. Drury, R. Amlôt, Social identity and intergroup relationships in the management of crowds during mass emergencies and disasters: recommendations for emergency planners and responders, in: Policing: A Journal of Policy and Practice, 2018 https://doi.org/10.1093/police/pay013.
[44] A. Ahmed, J. Sargent, Analysis of post-crisis twitter communication: a study of the iquique Chile earthquake, in: 25th Australasian Conference on Information Systems, 2014 (Auckland, NZ).
[45] A.K. Chatfield, H.J. Scholl, U. Brajawidagda, Tsunami early warnings via Twitter in government: net-savvy citizens' co-production of time-critical public information services, Govern. Inf. Q. 30 (4) (2013) 377–386, https://doi.org/10.1016/j.giq.2013.05.021.
[46] A.L. Hughes, L.A.A.S. Denis, L. Palen, K.M. Anderson, Online public communications by police & fire services during the 2012 Hurricane Sandy, in: Paper Presented at the Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Canada, Toronto, Ontario, 2014 https://doi.org/10.1145/2556288.2557227.
[47] A. Ahmed, J. Sinnappan, The role of social media during Queensland Floods: an empirical investigation on the existence of multiple communities of practice (MCoPs), Pac. Asia J. Assoc. Inf. Syst. 5 (2013) 2.
[48] Brian Smith, Linjuan Men, Reham Al-Sinan, Tweeting Taksim communication power and social media advocacy in the Taksim square protests, Comput. Hum. Behav. 50 (2015), https://doi.org/10.1016/j.chb.2015.04.012.
[49] C. Castillo, Big Crisis Data: Social Media in Disasters and Time-Critical Situations, Cambridge University Press, 2016.
[50] G.H. Bressler, M.E. Jennex, E.G. Frost, Exercise 24: using social media for crisis response, Proceed. Int. J. Info. Syst. Crisis Res. Manag. 3 (4) (2012) 36–54, https://doi.org/10.4018/jiscrm.2011100103.
[51] S.L. Cutter, K.D. Ash, C.T. Emrich, Urban-rural differences in disaster resilience, Ann. Assoc. Am. Geogr. 106 (6) (2016) 1236–1252, https://doi.org/10.1080/24694452.2016.119474.
[52] T. Ludwig, C. Reuter, T. Siebigteroth, V. Pipek, CrowdMonitor: mobile crowd sensing for assessing physical and digital activities of citizens during emergencies, in: Paper Presented at the Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, Seoul, Republic of Korea, 2015.
[53] G.C. Kane, M. Alavi, G. Labianca, S.P. Borgatti, What's different about social media networks? A framework and research agenda, MIS Q. 38 (2014) 29.
[54] R. Liu, A. Suh, Factors influencing information credibility on social media platforms: evidence from Facebook pages. The thirds information systems international conference, Procedia Computer Sci. 72 (2015) 314–328, https://doi.org/10.1016/j.procs.2015.12.146.
[55] Adam Acar, Yuya Muraki, Twitter for crisis communication: lessons learned from Japan's tsunami disaster, IJWBC 7 (2011) 392–402, https://doi.org/10.1504/IJWBC.2011.041206.
[56] M. Cameron, R. Power, B. Robinson, J. Yin, Emergency Situation Awareness from Twitter for Crisis Management, 2012. WWW 2012 – SWDM'12 Workshop. Retrieved from https://www2012.universite-lyon.fr/proceedings/companion/p695.pdf.
[57] A.K.B.U. Chatfield, Twitter tsunami early warning network: a social network analysis of Twitter information flows. ACIS 2012: location, location, location, in: Proceedings of the 23rd Australasian Conference on Information Systems 2012, 2012, p. 10.

[58] Joo-Young Jung, Social Media Use and Goals after the Great East Japan Earthquake, vol. 17, First Monday, 2012, https://doi.org/10.5210/fm.v17i8.4071.
[59] Fujio Toriumi, Takeshi Sakaki, Kosuke Shinoda, Kazuhiro Kazama, Satoshi Kurihara, Itsuki Noda, Information Sharing on Twitter during the 2011 Catastrophic Earthquake, 2013, pp. 1025–1028, https://doi.org/10.1145/2487788.2488110.
[60] Nextdoor, How to Use Nextdoor in a Natural Disaster or Illness Outbreak, 2020 (Retrieved from:https://help.nextdoor.com/s/article/How-to-use-Nextdoor-in-a-natural-disaster?language=en_US).
[61] D.L. Bird, Megan, Katharine Haynes, Flooding Facebook? The use of social media during the Queensland and Victorian floods, Aust. J. Emerg. Manag. 27 (2012).
[62] R.E. Wilson, S.D. Gosling, L.T. Graham, A review of Facebook research in the social sciences, Perspect. Psychol. Sci. 7 (3) (2012) 203–220, https://doi.org/10.1177/1745691612442904.
[63] Facebook. Crisis Response, 2020. Retrieved from: https://www.facebook.com/help/141874516227713/?helpref=hc_fnav.
[64] E.Z. Kontos, K.M. Emmons, E. Puleo, K. Viswanath, Communication inequalities and public health implications of adult social networking site use in the United States, J. Health Commun. 15 Suppl 3 (Suppl 3) (2010) 216–235, https://doi.org/10.1080/10810730.2010.522689.
[65] R. Muttarak, W. Lutz, Is education a key to reducing vulnerability to natural disasters and hence unavoidable climate change? Ecol. Soc. 19 (1) (2014) https://doi.org/10.5751/ES-06476-190142.
[66] K.A. Borden, S.L. Cutter, Spatial patterns of natural hazards mortality in the United States, Int. J. Health Geogr. 7 (1) (2008) 64, https://doi.org/10.1186/1476-072X-7-64.
[67] D.M. Tootle, Disaster recovery in rural communities: a case study of southwest Louisiana, South. Rural Sociol. 22 (2007) 21.
[68] C.C. Kuhlthau, Inside the search process: information seeking from the user's perspective, J. Am. Soc. Inf. Sci. 42 (5) (1991) 361–371, 10.1002/(sici)1097-4571(199106)42:5<361::Aid-asi6>3.0.Co;2-#.
[69] M. Micheli, Social networking sites and low-income teenagers: between opportunity and inequality, Inf. Commun. Soc. 19 (5) (2016) 565–581, https://doi.org/10.1080/1369118X.2016.1139614.
[70] J. Witte, S. Mannon, The Internet and Social Inequalities, Routledge, New York, 2010 https://doi.org/10.4324/9780203861639.
[71] E. Hargittai, Second-Level Digital Divide: Differences in People's Online Skills, vol. 7, First Monday, 2002. Retrieved from http://firstmonday.org/issues/issue7_4/hargittai/index.html.
[72] S.P. Borgatti, C. Rob, A relational view of information seeking and learning in social networks, Manag. Sci. 49 (4) (2003) 432–445. Retrieved from www.jstor.org/stable/4133949.
[73] C. Tang, X. Wu, X. Chen, B. Pan, X. Yang, Examining income-related inequality in health literacy and health-information seeking among urban population in China, BMC Publ. Health 19 (1) (2019) 221, https://doi.org/10.1186/s12889-019-6538-2.
[74] M. Gardoni, M. Spadoni, F. Vernadat, Harnessing non-structured information and knowledge and know-how capitalisation in integrated engineering: case study at aerospatiale matra, Concurr. Eng. 8 (4) (2000) 281–296, https://doi.org/10.1177/1063293x0000800403.
[75] J.H. Park, B. Gu, A.C.M. Leung, P. Konana, An investigation of information sharing and seeking behaviors in online investment communities, Comput. Hum. Behav. 31 (2014) 1–12, https://doi.org/10.1016/j.chb.2013.10.002.
[76] D. Constant, S. Kiesler, L. Sproull, What's mine is ours, or is it? A study of attitudes about information sharing, Inf. Syst. Res. 5 (4) (1994) 400–421, https://doi.org/10.1287/isre.5.4.400.
[77] HCFCD, Impact and Response in Harris County Harris County Flood Control District, 2018 https://www.hcfcd.org/media/3000/hcfcd-harvey-impact-and-response-spreads-final-web-may-2018.pdf.
[78] E.S. Blake, D.A. Zelinsky, National Hurricane Center Tropical Cyclone Report, 2017. Retrieved from https://www.nhc.noaa.gov/data/tcr/AL092017_Harvey.pdf.
[79] National Weather Service (NWS), Hurricane Michael: October 10, 2018. National Oceanic and Atmospheric Administration (NOAA), 2018. Retrieved from:https://www.weather.gov/tae/HurricaneMichael2018.
[80] National Weather Service (NWS), Hurricane Florence: September 14, 2018. National Oceanic and Atmospheric Administration (NOAA), 2018 (Retrieved from: https://www.weather.gov/ilm/HurricaneFlorence).
[81] M.K. Lindell, S.N. Hwang, Households' perceived personal risk and responses in a multihazard environment, Risk Anal. 28 (2008) 539–556, https://doi.org/10.1111/j.1539-6924.2008.01032.x.
[82] US Census Bureau, 2018. (Retrieved from: https://www.census.gov/quickfacts/TX).
[83] B. Ripley, W. Venables, Package "Nnet", 2016 (https://cran.r-project.org/web/packages/nnet/index.html).
[84] A. Perrin, Digital Gap between Rural and Nonrual America Persists. FACTANK: News in the Numbers; PEW Research Center, 2019 https://www.pewresearch.org/fact-tank/2019/05/31/digital-gap-between-rural-and-nonrural-america-persists/.
[85] L.M. Holson, Nextdoor Is Betting a Social Network Can Still Be a Platform for Politics, The New York Times; Technology, 2018 https://www.nytimes.com/2018/07/13/technology/nextdoor-elections-politics-nyt.html.
[86] L.I. Iezzoni, E.P. McCarthy, R.B. Davis, H. Siebens, Mobility difficulties are not only a problem of old age, J. Gen. Intern. Med. 16 (4) (2001) 235–243, https://doi.org/10.1046/j.1525-1497.2001.016004235.x.
[87] A.W. Blume, Social Issues in Living Color: Challenges and Solutions from the Perspective of Ethnic Minority Psychology, Praeger; An Imprint of ABC-CLIO, LLC, Santa Barbara, California, 2017.
[88] R. Garett, E. Krueger, S. Young, Racial disparities in social media use, sexual risk behaviors, and HIV/AIDS stigma among men who have sex with men. HIV & AIDS Review, Int. J. HIV-Related Prob. 17 (3) (2018) 176–180, https://doi.org/10.5114/hivar.2018.78489.
[89] D. Sterrett, D. Malato, J. Benz, L. Kantor, T. Tompson, T. Rosenstiel, K. Loker, Who shared it?: deciding what news to trust on social media, Digital J. 7 (6) (2019) 783–801, https://doi.org/10.1080/21670811.2019.162370.
[90] M. Favaretto, E. De Clercq, B.S. Elger, Big Data and discrimination: perils, promises and solutions. A systematic review, J Big Data 6 (2019) 12, https://doi.org/10.1186/s40537-019-0177-4.
[94] K. Viswanath, Public communications and its role in reducing and eliminating health disparities, in: GE Thomson, F Mitchell, MB Williams (Eds.), Examining the Health Disparities Research Plan of the National Institutes of Health, Unfinished Business. Institute of Medicine, Washington, D.C, 2006, pp. 215–253.
[95] Ackerson, L. K., & Viswanath, K. (2009). The Social Context of Interpersonal Communication and Health. *Journal of Health Communication, 14*(sup1), 5-17. doi:10.1080/10810730902806836.
[96] Smith, A., Anderson, M. (2018). Social media use in 2018 (Report). Retrieved from http://www.pewinternet.org/2018/03/01/social-media-use-in-2018/ Google Scholar.
[97] Ottoni, R., Pesce, J. P., Casas, D. L., Jr, G., Meira Jr, W., Kumaraguru, P., & Almeida, V. (2013). Ladies first: Analyzing gender roles and behaviors in Pinterest. *Proceedings of the 7th International Conference on Weblogs and Social Media, ICWSM 2013*, 457-465.
[98] Jones, S., & Fox, S. (2009). Generations Online in 2009. Pew Research Centerhttp://www.pewinternet.org/Reports/2009/Generations-Online-in-2009.aspx.
[99] F. Vis, Twitter as a reporting tool for breaking news, Digital Journalism 1 (1) (2013) 27–47.
[100] Ryan, B. (2013) "Information seeking in a flood", Disaster Prevention and Management, Vol 22, No. 3, pp 229- 242.
[101] G. BrianSouthwell. networks and popular understanding of scienceand health: sharing disparities, Johns Hopkins University Pressand RTIPress, Research, BaltimoreTriangle, 2013, p. 106, 13 978-1-4214-1324.
[102] Duggan, M., Ellison, N., Lampe, C., Lenhart, A., Madden, M. (2015). Social media update 2014: While Facebook remains the most popular site, other platforms see higher rates of growth. Pew Research Center. Retrieved from http://www.pewinternet.org/files/2015/01/PI_SocialMediaUpdate20141.pdf.
[103] R. Gaspar, S. Gorjão, B. Seibt, L. Lima, J. Barnett, A. Moss, Tweeting during food crises: a psychosocial analysis of threat coping expressions in Spain, during the 2011 European EHEC outbreak, Int J Hum Comput Stud 72 (2014) 239–254.
[105] Takahashi B, Tandoc EC Jr, Carmichael C (2015) Communicating on twitter during a disaster: an analysis of tweets during typhoon Haiyan in the Philippines. Comput Hum Behav 50:392–398.
[107] S. Vosoughi, D. Roy, S. Aral, The spread of true and false news online, Science 359 (6380) (2018) 1146, https://doi.org/10.1126/science.aap9559.
[108] van Deursen, van Dijk, The digital divide shifts to differences in usage, New Media & Society 16 (3) (2013) 507–526, https://doi.org/10.1177/1461444813487959.
[109] Shumate, M. (2014). Social Networks and Popular Understanding of Science and Health: Sharing Disparities, by Southwell, Brian. *Health communication, 30*, 1-2. doi:10.1080/10410236.2014.885375.
[110] R. Li, A. Suh, Factors Influencing Information credibility on Social Media Platforms: Evidence from Facebook Pages, Procedia Computer Science 72 (2015) 314–328, https://doi.org/10.1016/j.procs.2015.12.146.
[111] M. Haight, A. Quan-Haase, B.A. Corbett, Revisiting the digital divide in Canada: the impact of demographic factors on access to the internet, level of online activity, and social networking site usage, Information, Communication & Society 17 (4) (2014) 503–519, https://doi.org/10.1080/1369118X.2014.891633.
[112] A. Grand, Social networks and popular understanding of science and health: Sharing disparities, Journal of Science Communication 13 (2014), https://doi.org/10.22323/2.13040701.
[114] T. Correa, Digital skills and social media use: how Internet skills are related to different types of Facebook use among 'digital natives, Information, Communication & Society 19 (8) (2016) 1095–1107, https://doi.org/10.1080/1369118X.2015.1084023.
[115] S.E. Chang, T. McDaniels, J. Fox, R. Dhariwal, H. Longstaff, Toward Disaster-Resilient Cities: Characterizing Resilience of Infrastructure Systems with Expert Judgments, Risk Analysis 34 (3) (2014) 416–434, https://doi.org/10.1111/risa.12133.
[116] M. Kaufmann, Resilience 2.0: social media use and (self-)care during the 2011 Norway attacks, Media, Culture & Society 37 (7) (2015) 972–987, https://doi.org/10.1177/0163443715584101.
[117] C. Peters, M.J. Broersma (Eds.), Rethinking Journalism: Trust and Participation in a Transformed News Landscape, 1st ed., Routledge, 2012 https://doi.org/10.4324/9780203102688.
[118] G. Blank, C. Lutz, Representativeness of Social Media in Great Britain: Investigating Facebook, LinkedIn, Twitter, Pinterest, Google+, and Instagram, American Behavioral Scientist 61 (7) (2017) 741–756, https://doi.org/10.1177/0002764217717559.
[119] J. Ahn, The effect of social network sites on adolescents' social and academic development: Current theories and controversies, Journal of the American Society for Information Science and Technology 62 (8) (2011) 1435–1445, https://doi.org/10.1002/asi.21540.