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On-demand ridesourcing for urban emergency evacuation events: An exploration of message content, emotionality, and intersectionality

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ABSTRACT

Evacuation mode choice has been researched over the past decade for disaster management and planning, focusing primarily on established modes such as personal automobiles, carpooling, and transit. Recently, however, on-demand ridesourcing has become a viable mode alternative, most notably through the growth of major transportation network companies, such as Uber and Lyft. The availability of this new transportation option is expected to have important implications for adaptive disaster response. The goal of this work is to investigate the influence of internal and external contextual factors on preferred ridesourcing applications during small-scale urban evacuations. A case study was conducted in the three most populous metropolitan areas in the United States. Data were collected using an internet-based stated preference survey, and a discrete choice model was estimated to analyze the 185 responses. Determinants of on-demand ridesourcing for evacuation include internal factors, such as interactions between race, gender, and income, and external contextual factors, such as the evacuation notification source, consequence severity, immediacy, evacuation distance, unfamiliarity of surroundings, and traveling with others. Findings are illustrated through three ridesourcing applications based on specific evacuation needs. Policy recommendations are provided for the design of equitable evacuation services, soft policy communication strategies, and public-private partnerships.

1. Introduction

Evacuation planning is a critical component of urban resilience. As our cities face more severe weather stressors induced by climate change, evacuations are becoming a more frequent occurrence. In 2018, wildfires led to the evacuations of residents in Arizona, California, Colorado, Oklahoma, and Oregon, and hurricanes necessitated evacuations in Alabama, the Carolina's, Florida, Georgia, Hawaii, and Virginia. To provide efficient and safe evacuation planning for all, it is crucial to manage traffic operations during mass evacuations, requiring a broader understanding of mode choice and evacuation behavior. Although existing research has considered evacuation mode choice, the primary focus has been on personal vehicles, carpooling, and public transit (e.g., Refs. [1–5]), overlooking an important contemporary movement of local disaster response facilitated by crowdsourcing and the sharing economy. On-demand ridesourcing is an emergent type of shared use mobility that allows passengers seeking rides to use smartphone applications to source for-hire registered drivers of private vehicles in real-time (e.g., Refs. [6–8]). As technological advances strengthen the use of crowdsourcing through expedient matching and reputation verification, the application of crowdsourced resources during disasters has become increasingly common. For instance, the crowdsourcing platform Crowdsource Rescue [9] has implemented mapping and global positioning system tracking technology to rescue and evacuate over 46,000 individuals since its deployment during Hurricane Harvey in 2017. Yet, the potential of ridesourcing in the context of evacuation remains largely unexplored.

In the rapidly evolving context of climate change, natural disasters, and disruptive mobility, we have entered a new era of disaster management. At present, the potential of the sharing economy for disaster response must be examined along with associated challenges, such as company liability, driver safety, and willingness to participate, among others, which will be discussed further in section 5. While acknowledging these concerns, the crowdsourcing framework has a remarkable capacity to innovate and improvise, establishing a promising system for adaptive disaster response arising from the platform's flexibility to accommodate individuals who desire to help and to rapidly deploy services in a time of need. Whittaker et al. [10] outlines many forms of disaster response, such as the spontaneous adoption of new functions by

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existing services. This category includes the temporary expansion of crowdsourcing organizations to absorb disaster response activities without being formally integrated into disaster management plans. This has been the method of operation exercised by ridehailing companies to date, but this piecemeal strategy may not be advisable long-term. Both ridehailing companies and drivers might be exposed to risks when choosing to supply rides inside evacuation zones, especially in the case of extreme hazards or as conditions progressively worsen. The manner in which informal crowdsourced rescue is considered within existing disaster response frameworks will greatly impact whether the potential surge capacity offered by evacuation ridesourcing will be a benefit or detriment to evacuation safety and efficiency.

By tapping into crowdsourced resources during a disaster event, urban areas can build resilience so long as important considerations are made in advance [11]. In the case of ridesourcing, its inclusion in evacuation planning may enhance the resilience of transportation systems by providing dynamic adaptability to rapidly evolving conditions, maintaining functionality under adverse circumstances when established modes may be unavailable or overloaded, offering agile connectivity throughout the system for carless populations, and freeing emergency personnel to focus on more specialized care. Notably, the resilience of a networked system (such as transportation) relies on both its inherent coping capacity under ordinary operating conditions and its potential to adapt quickly during disruptive events (e.g., Refs. [12–14]). The former is provided by the system's topology and operational qualities, while the latter refers to its flexibility to respond to changing circumstances and demands. The focus on adaptive capacity is echoed by Harrald [15] who highlights that in addition to *discipline* (i.e., the focus and efficiency that comes from well-defined and pre-planned processes), disaster response needs to be *agile* or consist of the creativity and adaptability necessary for quick coordination, collaboration, and communication when faced with unforeseen events.

Ridesourcing is an increasingly familiar and relied upon mode alternative that may be suited for disaster response due to its on-demand flexibility and supply scalability. This ability to respond to changing conditions is also known as adaptive capacity and is an important component of resilience. By developing adaptation-oriented strategies, decision-makers can improve the response of regulated systems and enhance their resilience to disruptions. As such, some ridehailing companies are beginning to establish permanent teams dedicated to centralized disaster response to replace case-by-case decision-making which is often subject to post hoc review and fare reimbursement [16]. With these efforts in mind, the goal of this research is to examine the role of ridesourcing for relocation and emergency applications. The first objective is to study the effects of external contextual factors and internal motivations for a range of hypothesized urban emergencies on the general propensity to use ridesourcing to relocate. Second, we identify preferred applications of on-demand ridesourcing for different contexts and population groups. Third, we discuss practical implications of the findings. By outlining contextually-dependent preferred applications of evacuation ridesourcing, policymakers may use these findings as a guide when developing pre-planned, community-tailored evacuation strategies to improve accessibility and lessen the risk of exacerbating inequalities during a disaster.

The remainder of this paper is organized as follows. Section 2 discusses literature related to evacuation choice modeling, mode choice determinants, on-demand ridesourcing, hot-state decision-making and emotionality, and warning messages. Section 3 describes the methodology used to collect and analyze data including definitions of model parameters. Section 4 presents and discusses findings from the model estimation. Section 5 emphasizes research implications for planning and policymaking. Section 6 summarizes the conclusions of the study.

2. Background

2.1. Evacuation choice modeling

Planning for evacuations can be supported by many modeling approaches. Evacuation decision-making is often modeled using the classic four-step travel demand framework, which begins with trip generation to estimate how many individuals will evacuate and at what time, followed by origin-destination distribution, mode choice, and finally, route assignment (e.g., Refs. [17,18]). To investigate the process for deciding whether to evacuate and the associated timing, researchers have used binary logit models with multivariate explanatory variables [19], repeated binary logit models [20], household-level discrete choice models [21], household-level mixed logit models [22], household-level nested logit models [23], and multinomial multilevel modeling using Hierarchical Generalized Linear Modeling to account for social network effects [24]. A review of evacuation decision determinants is provided by Huang et al. [25]. For destination decision-making, studies have applied gravity-based choice models [20], spatially correlated logit models [26], and ANOVA analysis paired with temporal-spatial pattern mapping [27]. To study route assignment, researchers have used dynamic traffic simulations incorporating compliance behavior [28], hybrid route choice models [20], binary route choice models [29], and mixed logit models [30]. Interdependencies between decisions also have been considered, such as through the use of copula-based joint model structures to investigate evacuation destination and departure time interdependencies [31], as well as through the application of structural equation models to examine the interrelationship between the decision to evacuate and destination choice [32].

The importance of these models lies in their ability to improve evacuation planning and management (e.g., Refs. [33,34]). Yet, to accurately estimate evacuation models [35] and dynamic network simulations [36], the right determinants must be identified for trip generation, departure timing, and the choices of destination, mode, and route, which requires knowledge of significant behavioral parameters gained through survey-based behavioral studies [37]. Oversimplified behavioral assumptions can lead to significant inaccuracies, such as the underestimation of evacuation travel times generated by user equilibrium assignment [38]. The incorporation of decision-making behavior into evacuation simulations is exemplified in an "agent-based regional evacuation simulator coupled with user enriched behavior" that combines household decision-making models with traffic flow models [39]. Coupled modeling is also observed in fire and traffic simulations using spatial-temporal geographic information system (GIS) methods to more accurately estimate evacuation times to inform the issuing of wildfire evacuation notices [40].

Acknowledging these advancements in evacuation modeling and simulation, the challenge remains to examine evacuation mode choice in the context of evolving mode alternatives, mobility styles, and needs. Several studies have sought to broaden the analysis to overlooked groups and modes to identify needed evacuation policies. For example, Renne et al. [41,42] and Renne [43] examined the evacuation of special needs populations, and Yin et al. [44] studied the role of emergent connected vehicle technology for coordinated evacuation of carless and limited-mobility individuals. To capture the importance of multimodal planning, evacuation models have advanced to include the use of mixed-integer linear programming to optimize evacuation routes for transit-dependent individuals [45], agent-based simulations of transit bus evacuation [46], mathematical programming formulations to optimize evacuation bus routing [47], multimodal micro-simulations combined with GIS-based network analysis to simulate rail transit and walking evacuations [48], dynamic sequential assignment to model the evacuation of pedestrians, private vehicles, and buses [49], and integer linear programming combined with ArcGIS-based analysis to map the vulnerabilities of transit-dependent populations during hurricane evacuations [50]. However, as we enter a new era of innovative mobility options, the concept of multimodality needs to be expanded beyond the use of buses, rail, and walking for evacuation. Evacuation models must now begin to incorporate the phenomenon of on-demand shared use mobility.

2.2. Evacuation mode choice determinants

Several studies over the past decade have examined evacuation mode choice, covering a range of locations (e.g., Alabama, Florida, Louisiana, Mississippi, and Texas), mainly focusing on hurricane evacuation events, such as Hurricanes Irma, Ivan, Katrina, Lili, Rita, and Wilma (e.g., Refs. [1,3–5,51,52]), and utilizing two major categories of data (e.g., revealed preference (RP) and stated preference (SP)). Findings from these evacuation mode choice studies suggest that hurricane evacuees use a personal vehicle at very high shares such as 90% (e.g., Refs. [1,52]), 89% [4], or 73% [5]. The second most commonly used mode is often carpooling at relatively low shares around 10% [5], 9% [1], or 6% [4]. During hurricane evacuations, being female decreases the likelihood of using a special evacuation bus, and being single or having a lower income decreases the likelihood of taking a taxi to evacuate [3]. Determinants of the number of vehicles evacuated per household during hurricane evacuations include the number of registered vehicles and eligible drivers per household [51]. This literature analysis led to a number of insights for the current analysis.

The current literature on evacuation mode choice has been rooted in hurricane evacuations, which entail specific features that do not carry over to all types of evacuation events. For example, hurricane evacuations usually offer advanced warning and in this way are different from no-notice events like wildfires and hazardous waste spills. While the literature on hurricane evacuation mode choice provides insights into decision-making strategies in a specific context, these findings cannot be directly applied to all evacuation scenarios, such as the no-notice and short-notice evacuation scenarios examined in this study. By controlling for different types of evacuation events, the present study examines the effects of varying urgency, situational constraints, and individual characteristics on strategies for optimal decision-making.

When studying evacuation mode choice, the use of RP surveys requires the availability of data on the recent occurrence of a real evacuation and are, therefore, somewhat uncommon. To compensate, SP hypothetical surveys are often conducted with an acknowledgement of their inherent limitations. While many published works have used SP surveys to investigate hypothetical evacuation scenarios (e.g., Refs. [2,3,5,53]), to the best of the authors' knowledge, mode choice models have not yet been applied to identify the determinants of using on-demand ridesourcing for evacuation. Additionally, few studies to date have examined the influence of contextual factors reflecting evacuation events with differing characteristics and degrees of urgency on mode choice. This summary focuses specifically on evacuation mode choice. For reviews on other categories of evacuation choices, please refer to Murray-Tuite and Wolshon [54]; Toledo et al. [19]; or Wong et al. [52].

2.3. On-demand ridesourcing

Although evacuation mode choice studies considering ridesourcing remain scant in the literature, several recent studies have investigated the adoption of ridesourcing for general travel purposes, providing some insights into ridesourcing user profiles under ordinary conditions. For example, ridesourcing users are typically male, highly educated, older Millennials, individuals who travel more by plane and conduct long-distance business, frequently travel with companions, regularly use smartphone transportation apps, use taxis and carshare services, own fewer vehicles compared to taxi users, and have attitudes reflecting concern for the environment, acceptance of new technologies, and desire for variety (e.g., Refs. [7,8,55,56]). Although these general user profiles have been identified, the effects of contextual factors on the preference for ridesourcing during an evacuation remain unknown. However, some intuition may be gleaned by considering the determinants of ridesourcing for general trip purposes. Findings show that such determinants include short wait time and travel time, as well as the ease of hailing and convenient payment processes [7], although contextual factors are expected to have an effect on these determinants, as well. Current policy debates regarding everyday challenges related to equity issues (e.g., discrimination, the digital divide, data privacy, security, and worker exploitation), economic efficiency, and environmental sustainability (e.g., Refs. [8,57,58]) may provide some guidance for considering policymaking and regulations for ridesourcing services during disaster events, although challenges in a disaster context should not be assumed limited to these.

Building on real-world experience, some sharing economy companies have already implemented disaster response and recovery practices. For example, although Uber has cycled through a variety of policies regarding surge pricing, the company offered one free ride per user to or from evacuation centers in Hawaii during Hurricane Lane in August 2018 [59] and free rides up to $25 in value to evacuation shelters in Florida, Georgia, and Alabama during Hurricane Michael in October 2018 [60]. Lyft offered free rides up to $30 in value in the Carolina's during Hurricane Florence in September 2018 [61], one free ride per user up to $15 in value during Hurricane Michael in October 2018 [62], and free rides in California due to wildfires in November 2018 [63]. Lyft has branded helping those in need as part of its company mission through its *Wheels for All* program and has partnered with Facebook Community Help in a collaborative effort to provide crisis response [64]. Uber has developed a *Global Security Center* which aims to provide disaster assistance for local communities [65]. Airbnb has also launched a crisis response program called *OpenHomes* which provides free temporary housing to those in need of disaster relief, medical stays, and refugee housing [66]. In light of these actions and expressed interest, research on crowdsourced evacuation resources and collaborative disaster response strategies is needed to assist with governmental planning, policymaking, and the development of public-private partnerships within a broader resilience framework.

It is unknown how findings in the existing literature will translate to the use of ridesourcing in disaster evacuation contexts, although the practice is already underway. Therefore, the objective of this study is to consider the current findings while exploring the space further to disentangle internal and external contextual influences on the demand for ridesourcing in evacuation contexts. To the best of the authors' knowledge, only two other studies have been conducted in this research area. Both use declared data to address the fundamental question of whether drivers would be willing to provide evacuations rides, the methodological limitations of which are addressed in subsection 5.5. The first article focuses on the use of ridesourcing for no-notice evacuations in China to reduce intermediate evacuation trips, revealing that driver willingness is stronger among single, young, male drivers, while driver unwillingness stems from concerns regarding the need to pick up family members in affected areas [53]. The second report examines the use of transportation network companies for evacuation during three recent wildfires in California, finding the behavior to be extremely uncommon [67]. However, the study also shows that a strong majority of drivers are willing to share personal transportation while evacuating (59%–72%) and that the top associated concerns are safety/security, responsibility, space capacity, extended evacuation times, and route deviation [67]. The present study builds upon these early indications that some drivers are willing to supply evacuation rides. The specifics of evacuation ridesourcing demand is explored herein by systematically modeling the determinants of ridesourcing preferences and the effects of interactions between internal and external contextual factors on those determinants.

2.4. Hot-state decision-making and emotionality

To capture the propensity to use ridesourcing during an evacuation with increased realism, we consider two types of contextual effects: the external context of a disaster scenario and the internal state of the decision-maker. Stress and emotion can have significant effects on the decision-making process, and these effects are often overlooked in hypothetical choice experiments, such as SP evacuation surveys. However, in this study, by measuring emotional intensity, we are able to examine the effect of respondent emotionality on response strategy. In this way, we can monitor both the effect of emotionality on the perceived urgency of the hypothetical scenarios and whether emotionality has a significant effect on evacuation mode choice. The relationship between emotionality and perceived urgency is an important consideration in SP surveys due to what Thaler and Sunstein [68] describe as the "hot-cold empathy gap", which refers to one's inability to comprehend, while in a cold-state, the alteration of one's behavior and preferences as experienced in a hot-state, a concept originally developed by Loewenstein [69]. The term "hot-state" describes a condition of heightened emotion that leads one to act impulsively on visceral desires [70]. This suggests that while in a cold-state, we are poor predictors of our own hot-state responses and behaviors, presenting a challenge to hypothetical surveying. In evacuation settings, hot-state decision-making is likely to occur due to the presence of strong emotions, such as increased fear, anger, and sadness. These emotions can alter the processes by which decisions are made, for example by switching from a decision-making rule driven by utility maximization to one of regret minimization [71]. It is important to note that while stress levels may elevate, people rarely, if ever, panic in response to emergency events (e.g., Refs. [72–77]). In fact, rather than panicking and behaving irrationally, it has been shown that in these scenarios individuals continue to engage in rational decision-making processes (e.g., Refs. [72,78–80]).

Over the past decade, research has examined the effects of emotion on decision-making. Emotion is often measured in one of two ways: as an aggregate emotional intensity or as discrete emotional states. *Emotional intensity* refers to individual-level differences in the experienced strength of emotions [81]. In the fields of health, economics, and policy, findings have shown an effect of emotional intensity on preferences [82], a correlation between emotionality and the use of compensatory versus non-compensatory decision rules [83], and a relationship between extreme emotional states and deviations from random utility maximization theory [84].

Many studies on risk perception and message-processing have measured the effects of specific discrete emotional states, such as the four primary negative emotions of anger, sadness, fright, and anxiety, on risk perception and decision-making (e.g., Refs. [85–88]). Studies in this area have shown that emotion predicts adaptive behavior and behavioral avoidance [89], as well as compliance with emergency messages [90]. Furthermore, studies using the measurement of discrete emotions have found that different negative emotions, such as fear and anger, can have highly differentiated effects on perception or judgment [88]. Specifically, fear has been shown to be associated with greater uncertainty and situational control, while anger has been associated with greater certainty and individual control [88]. Additionally, emotions associated with different levels of certainty have been shown to lead to different types of decision processing (e.g., Refs. [91,92]). Structural equation modeling has been applied to model the effects of emotion according to three sub-scales (e.g., fear, anger, and fear of harm), revealing a significant and positive effect on decision clarity [90].

In the field of transportation, research considering emotionality has mainly focused on the effects of daily travel satisfaction on emotion, mood, and wellbeing (e.g., Refs. [93–95]), while some research has incorporated emotion and personality into crowd evacuation simulations to generate more realistic behaviors [96]. However, the inclusion of an emotionality scale in an evacuation mode choice study remains novel in this field.

2.5. Warning messages

The present study considers the influence of warning message content on mode choice, drawing on findings from earlier publications regarding the effects of emergency communication on evacuation decision-making. Earlier research has shown that recipients of warning messages proceed through a series of six stages that shape decision-making and behavior: hearing-perceiving, confirming/milling, understanding, believing, personalizing, and responding/decision-making (e.g., Refs. [75,97,98]). Three elements are important to consider when examining the impacts of warning messages on decision-making and response: content, style, and receiver characteristics [75].

Warning message content incorporates numerous elements, including the hazard itself, the location, instructions, timing, and message source (e.g., Refs. [75,97,99–103]). Such content can have significant effects on decision-making. For example, when comparing hazard-based, impact-based, and fear-based messages, those of *high-impact* (i.e., those emphasizing impacts on buildings and property) and *fear-based* messages (i.e., those emphasizing impacts on human life) were shown to have a positive effect on the intention to evacuate, risk perception, and response efficacy [104]. Furthermore, message length has attracted a great deal of research, comparing so-called "terse" emergency alerts (containing a maximum of 90 characters) and Twitter-length warnings (typically limited to 140 characters) to long-form messages (usually over 1000 characters) (e.g., Refs. [89,90,99–101,103,105,106]).

The warning style may refer to the message specificity, consistency, certainty, clarity, accuracy, completeness, and the channel through which the message is received (i.e., [75,99–101,107]). These factors also have a notable impact on decision-making. For instance, the inability to interpret messages, a belief that the message is inaccurate, and the experience of "warning fatigue" from receiving messages too frequently have each been shown to contribute to the decision to not evacuate [108].

Finally, receiver characteristics may include environmental cues, social setting, social ties, social structure, psychological factors, and pre-warning perceptions [75]. Considering environmental cues, research has shown that when an emergency event does not provide adequate time to issue official warning messages, individuals often rely on environmental cues and informal social networks to gather information to support decision-making [109]. One's social setting may be embedded in the local culture, which impacts informal social networks and common language, all of which should be accounted for when designing risk communication strategies [110]. Social structure can mandate the flow of *implicit* information (i.e., community-based, orally-transmitted information), which should be integrated with *explicit* information (i.e., governmental information that can be documented and distributed) to improve risk communication and facilitate bottom-up disaster response planning [111]. Regarding social status, research has shown that younger individuals and females typically respond more quickly to evacuation warnings, ethnic minorities are less trusting of warnings (especially when provided by law enforcement), and lower income respondents receive fewer warnings from trusted sources [112].

The present study investigates the effects of several warning message elements, covering content, message style, and receiver characteristics on evacuation mode choice. The examined elements of message content include the hazard type, location, instruction, evacuation timing, and message source. The message style is embedded in the message source, representing the channel through which the message is received (i.e., authority versus rumor), which may affect perceptions of certainty and accuracy. Lastly, the considered receiver characteristics include sociodemographics, emotionality, and attitudes toward the sharing economy.

2.6. Literature takeaways for experimental design

The current research builds on the foundational works discussed above, including the use of descriptive hypothetical evacuation scenarios (e.g., Refs. [2,113]), an emotional intensity scale (e.g., Refs. [82–84]), and an SP evacuation mode choice survey (e.g., Refs. [2,3,5]). A discrete choice model is used to examine the combined influences of external contextual factors (such as evacuation notification strategies) and internal contextual factors (like emotionality and intersectionality) within a currently evolving mobility context that includes on-demand services for emergency evacuation. This work proposes three contextually-dependent applications of ridesourcing for evacuation to assist in the development of pre-planned ridesourcing services for equitable disaster response.

3. Methodology

3.1. Survey design

The SP survey contained eight evacuation scenarios with varying degrees of urgency to investigate the effects of six contextual factors on evacuation mode choice. The eight scenarios are provided in Table 5 in Appendix (section 7). The small-scale evacuation scenarios consisted of a blackout, a bomb threat, a hazardous waste spill, a disease outbreak, a blizzard alert, a flooding alert, a protest, and an unscheduled stadium concert release. While some contextual factors are implicitly contained in the nature of the evacuation event, the following factors were explicitly varied in the message content for each scenario, because they have been shown to have a significant effect on warning message response [75]: the hazard type, hazard distance, predicted location of hazard, response time, message source, and social setting. For each event respondents were instructed to select their preferred mode among seven available transportation options: personal vehicle, carpool, train, bus, ridesourcing, taxi, or active transportation (e.g., walking or bicycling). Multiple modes could be selected to represent mode chaining. Respondents were also asked, “When imagining this scenario, what level of urgency did you feel?” They could answer on a four-point scale from “extremely high” to “extremely low”. An additional four attitudinal questions and four emotional intensity scale questions were presented, as listed in Table 6 in Appendix (section 7). By including questions selected from a reduced emotional intensity scale adapted by Geuens and de Pelsmacker [114] from the original emotional intensity scale created by Bachorowski and Braaten [115]the relationship between the emotionality of each respondent and the degree of urgency with which each hazard scenario was perceived could be examined. Finally, each respondent was asked to answer six socio-demographic questions (i.e., residential location, gender, age, race, employment, and income). Opportunities to submit comments and feedback were provided throughout the survey.

The evacuation scenarios were selected using a fractional factorial design to capture six context factors of two levels each within eight scenarios. The factorial design was performed using the *choiceDes* package in *R* with the *dcm.design* function [116] to ensure attribute level balance. The six message factors examined in the choice experiment were *sociality* (with friends or alone), *familiarity* (in a familiar or unfamiliar location), *information source* (authority or rumor), *immediacy* (leave immediately or within 30 min), *severity* (severe or mild consequences), and *evacuation distance* (3 km or 16 km). In this way, the choice experiment accounted for both scenario-specific attributes and notification strategies. Due to the novel nature of the survey design, which emphasizes evacuation context, the effects of mode alternative attributes (such as travel time, cost, and reliability) were not explicitly measured in this study. By embedding the contextual factors directly into the hazard narratives, the scenarios subtly and selectively controlled for contextual factor effects, similar in design to a study of contextual influences on food choice by Jaeger and Rose [117].

The survey was created using Qualtrics software [118]. It was distributed through a Northwestern University engineering list serve and on Amazon’s Mechanical Turk (MTurk) seeking respondents from New York City, Los Angeles, and Chicago. A small monetary incentive was provided to respondents using the MTurk interface. A total of 185 useable responses were received. Given eight choice experiments, 1480 observations were considered in the analysis. The surveyed population is compared to actual population demographics provided by the United States Census Bureau [119] in Table 1, indicating an acceptable socio-demographic representation, with some exceptions including a higher representation of younger individuals and a lower representation of low income respondents.

Limitations of survey distribution through MTurk have been considered, such as lower attention to experimental materials [123]. Therefore, screening questions were included to check for attention and language comprehension. The attention check consisted of embedded instructions to select a specific response for a certain question in the first half of the survey. Failure to select the correct response resulted in removal of the respondent from the survey. This method of directed queries has been shown effective in detecting inattentive respondents [124]. Completion time and response patterns were also taken into account when verifying response quality.

Table 1
Socio-demographic comparison between surveyed population and actual population.

	Survey	New York	Los Angeles	Chicago
Residence				
New York	26.5%			
Los Angeles	35.7%			
Chicago	37.8%			
Population		20.3 M	13.4 M	9.53 M
Households without vehicle		22.2%	3.3%	6.1%
Registered ridesourcing drivers		89,000[a]	100,000[b]	67,000[c]
Gender				
Male	55.7%	48%	49%	49%
Female	44.3%	52%	51%	51%
Age				
Under 18		21.5%	21.9%	23%
18–24	17.8%	8.9%	9.6%	9.12%
25–34	54.6%	14.8%	15.8%	14.37%
35–44	14.1%	13.1%	13.5%	13.25%
45–54	8.1%	13.7%	13.7%	13.4%
55–64	3.8%	12.8%	12%	12.8%
65 +	1.6%	15.3%	13.5%	14.1%
Race				
White	63.8%	46.1%	29.4%	52.8%
Hispanic		24.6%	45.2%	22.3%
African American	9.2%	15.6%	6.3%	16.3%
Asian	17.8%	11.3%	16%	6.5%
American Indian	1.1%	0.1%	0.2%	0.08%
Hawaiian	0.5%	0.02%	0.2%	0.03%
Two or more	3.2%	1.7%	2.4%	1.8%
Other	4.3%	0.7%	0.3%	0.2%
Employment				
Full-time	62.7%	58.9%	55.5%	59.2%
Student	20%			
Part-time	9.2%	16.1%	18%	17.7%
Unemployed	8.1%	25%	26.6%	23%
Income				
Less than $10k	4.9%	10.4%	10.8%	11.6%
$10k - $19,999	3.8%	12.6%	13.3%	12.5%
$20k - $29,999	8.1%	13.1%	14.2%	13.7%
$30k - $39,999	20.5%	11.6%	11.9%	12.6%
$40k - $49,999	10.3%	9.7%	9.2%	10.1%
$50k - $59,999	17.3%	8.7%	7.2%	8.44%
$60k - $99,999	16.8%	19.5%	17.8%	19.1%
$100k - $149,999	6.5%	8.3%	8.9%	7.2%
$150k +	7.6%	6.2%	6.7%	4.8%
No answer	4.3%			

[a] O’Brien [120].
[b] DriversUnited [121].
[c] Channick [122].

3.2. Modeling methods

The econometric approach adopted to analyze the evacuation choice experiment data is part of the discrete choice random utility maximization framework. To examine respondents' reactions to ridesourced evacuation in different settings, random parameter discrete choice models [125] were estimated using the open source freeware Bison-Biogeme [126]. Random parameter logit models employ a mixing distribution or density function of one or more coefficients. This allows the stochastic (or unobserved) component of a utility function to vary by individual, which enables the model to capture unobserved heterogeneity across respondents. The random parameter framework was selected to examine any systematic differences in the preferences for new evacuation mode options (like ridesourcing) compared to more established modes.

The study of ridesourcing for relocation in response to emergencies mirrors earlier research on status quo effects. In "status quo" experiments, research has identified an asymmetry between preferences for the status quo alternative versus less-familiar alternatives [127]. The higher noise or variance associated with novel options may be attributed to higher levels of uncertainty regarding a more hypothetical alternative and less well-formed preferences [128].

In our model framework, each utility function contains an alternative specific constant (ASC) or intercept that represents the relative general propensity of respondents to select that alternative. In conditional logit models, this term is part of the systematic component of the utility function and is assumed to be the same for all respondents. The model proposed herein uses a random coefficient to specify the intercept of the ridesourcing utility function, following a method described by Day et al. [128] and Marsh et al. [127]. The inclusion of this individual-specific random intercept term captures the differences in preferences across a population. The work builds on earlier random parameter applications specifically aimed at capturing differences in how alternatives are perceived, including status quo effects (e.g., Refs. [127–137]).

The evacuation mode choice process is represented by a systematic component V_i and an error term ε_i that varies by individual i and for each alternative. In terms of modeling, this means applying two error terms to capture the alternative-specific variance: the standard conditional logit independently and identically distributed (IID) type 1 extreme value distribution (EV1) error for each option, plus a randomly distributed error component for the ridesourcing intercept (e.g., Refs. [136,137]). The error term in the model ε_i is independent from the random coefficient, and it varies by individual i for each alternative. For all alternatives, the error term retains its specification from the conditional logit model, that is IID EV1 across all alternatives, also known as a Gumbel distribution [136]. This error specification is expressed as $\varepsilon_i \tilde{} \; IID\ EV(0, \mu)$. The random coefficient is expressed as an individual-specific intercept $ASC_{i,Ridesource}$, comprising both a systematic and stochastic element, $ASC_{Ridesource} + \alpha_i$, respectively, where $ASC_{Ridesource}$ is the population mean and α_i is the normally distributed stochastic dispersion, specified as $\alpha_i \tilde{} \; N(0,\sigma)$ with a zero mean and an estimated variance of σ^2 (e.g., Refs. [125,128]). While any mixing distribution may be assigned to capture the variance of the random term (e.g., uniform, triangular, gamma, etc.), the most common are normal and log-normal (e.g., Refs. [129,136, 138]). The random coefficient used in this model was specified as normally distributed to capture the different propensities of respondents to accept or reject ridesourcing.

The final model includes three mode alternatives, two main effects parameters, seven interactions, and one random coefficient assigned to the intercept of the ridesourcing utility expression. The choice set is grouped to represent three modes: established modes, ridesourcing, and the combined use of both mode types in sequence. Alternative specific constants are estimated for ridesourcing and mixed modes, while the ASC for established modes was taken to be a reference and was, therefore, fixed to zero. The model parameters are defined in Table 2, and the final utility specification after model testing is defined in Equations (1)–(3).

$$V_{i,Established} = ASC_{Established} + \beta_{Under35} Under35_i + \beta_{Unfamiliar} Unfamiliar_i + \beta_{Far,Chicago}(Far_i \times Chicago_i) \quad (1)$$

$$V_{i,Ridesource} = ASC_{i,Ridesource} + \beta_{Severe,NewYork}(Severe_i \times NewYork_i) + \beta_{Immediately,Chicago}(Immediately_i \times Chicago_i) \quad (2)$$

Table 2
Model parameters.

Mode alternatives	
Established	*Drive* (e.g., car, truck, motorcycle); *Carpool driven by someone you know* (e.g., family, friend, neighbor, colleague); *Train* (e.g., commuter, light rail, tram); *Bus* (e.g., intercity, rapid transit, shuttle); *Taxi* (e.g., cab); *Active transport* (e.g., walk, bicycle)
Ridesource	*Ridesourcing* (e.g., Uber, Lyft)
Mixed Modes	Any combination of established modes and ridesourcing in sequence
Parameters (contextual factor dummy variables)	
Respondents were instructed to imagine a hypothetical evacuation scenario based on the	
Authority	information source was an authority such as an emergency management system, a city official, etc. when equal to one; information source was an overheard rumor from an unidentified individual when zero
Far	clear a 16 km radius when equal to one; clear a 3 km radius when zero
Immediately	required to evacuate immediately when equal to one; required to evacuate within 30 min when zero
Friends	with two friends when equal to one; not with anyone else you know when zero
Severe	consequences of not evacuating were implied to be severe when equal to one; consequences were implied to be mild when zero
Unfamiliar	in an unfamiliar location when equal to one; in a familiar location when zero
Parameters (socio-demographic dummy variables)	
A "1" indicates the respondent … and "0" indicates otherwise.	
NewYork	resides and/or works in New York City
Chicago	resides and/or works in Chicago
Female	is a self-identified female
Under 35	is 34 years or younger
Black	is of a Black ethnicity
Nonwhite	is of an ethnicity other than White
LowIncome	earns a gross annual household income of $19,999 or less

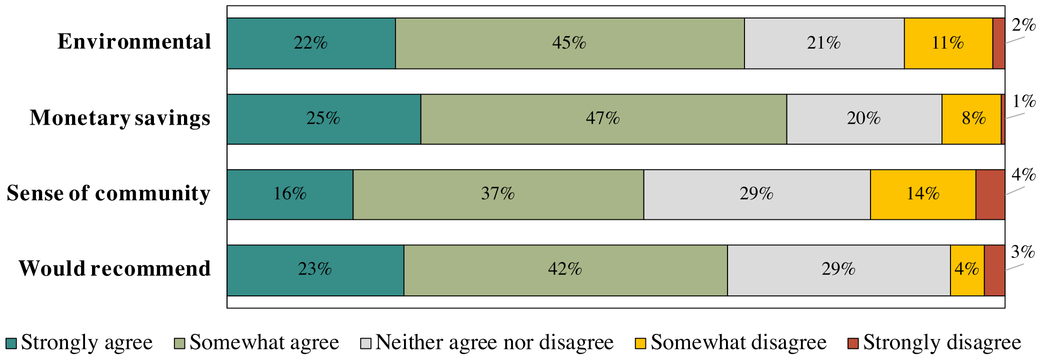

Fig. 1. Attitudes toward sharing economy.

$$V_{i,MixedModes} = ASC_{MixedModes} + \beta_{Black,LowIncome}(Black_i \times LowIncome_i) + \beta_{LowIncome,Authority}(LowIncome_i \times Authority_i) + \beta_{Female,Nonwhite}(Female_i \times Nonwhite_i) + \beta_{Nonwhite,Friends}(Nonwhite_i \times Friends_i) \quad (3)$$

4. Results

The following discussion explores our research questions. First, we examine the general acceptability of ridesourcing as a function of contextual (i.e., external and internal/personal) variables. Second, we outline three applications for ridesourcing in an evacuation setting emerging from the model results and supported by marginal effects estimates. Finally, a broader discussion in line with the third objective is continued in section 5.

4.1. Internal context

Internal context considers attitudes, perceptions, and emotions. The attitudes of the majority of respondents reflected positive views of the sharing economy, as shown in Fig. 1. The sharing economy was defined in the survey as “an exchange of goods and services among peers. Examples include Uber, Lyft, Airbnb, TaskRabbit, Turo, Instacart, Deliv, etc.” The greatest majority of respondents reported believing that the use of sharing economy services saves money, followed by believing that the use of sharing economy services is an environmentally-friendly form of consumption and that they would recommend sharing economy services to friends. The smallest majority believed that participation in the sharing economy improves one’s sense of community. These findings suggest that one of the main motivating factors for using sharing economy services in general is financial rather than a feeling of social connectedness.

To determine evacuation mode preference, the choice experiment instructed respondents to assume their preferred mode was available for

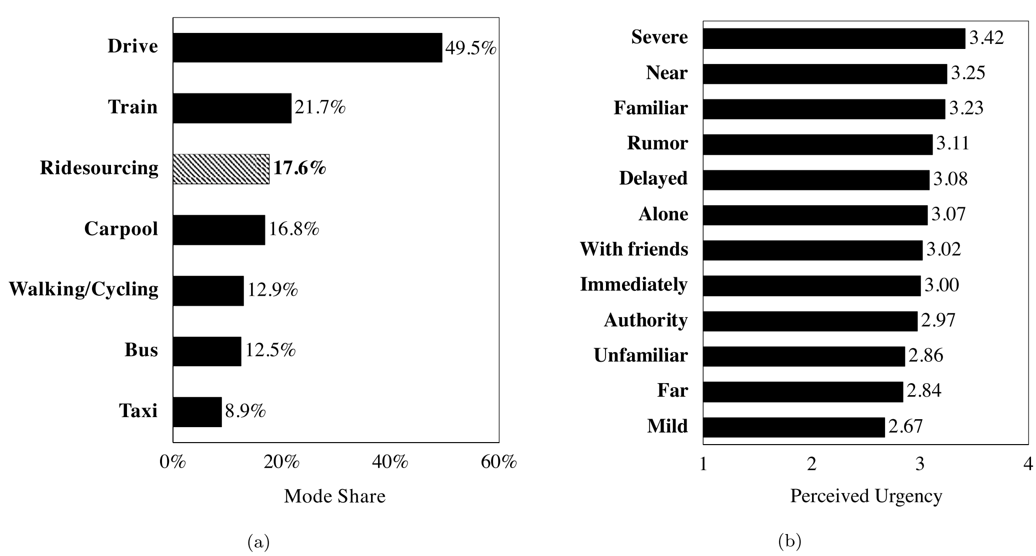

Fig. 2. (a) Preferred evacuation mode share, and (b) Effect of contextual factors on perceived urgency.

evacuation, as specified in Table 5 in Appendix (section 7). As such, the findings reveal preferences as opposed to forecasting real-world outcomes. Ridesourcing was selected as a preferred evacuation mode 17.6% of the time, as shown in Fig. 2a. This number should not be taken as a reliable market-share forecast due to the hypothetical nature of this data [139]. Yet, SP models are better than RP at capturing responses to changes in attributes due to their controlled design. Thereby, the results provide insight into the marginal effects that different contexts exert on the choice of evacuation modes. It is important to recall that multiple modes could be selected for any scenario to reflect evacuation mode chaining. Hence, the percentage totals do not sum to one hundred across all seven modes.

Although many factors embedded in the nature of each evacuation event may lead to different mode choice strategies, the survey inquired specifically about respondents' perceived urgency. Fig. 2b shows the effect of the scenario-specific contextual factors on the degree of urgency perceived. The relationship between perceived urgency and external contextual factors of the evacuation scenarios reveals that the contextual factor of *severe consequences* generates the greatest sense of urgency on average across respondents. This factor was represented in the choice experiment by potentially life-threatening hazardous events, such as the report of a bomb, as opposed to scenarios with presumably milder consequences, such as a no-notice release of a stadium concert. Interestingly, when the source of the evacuation notification is a *rumor* with incomplete information, it inspires a greater sense of urgency compared to when the source is an official authority, such as an emergency management system. This finding suggests that the provision of partial information may increase a recipient's perception of urgency.

Emotionality was not found to be a significant determinant of mode choice in the discrete choice model, suggesting that individual-level emotional intensity as measured herein may not lead to significantly different response strategies in evacuation mode choice contexts. However, a modest positive trend between emotionality and perceived urgency was found when analyzing the average perceived urgency across the eight scenarios for each respondent. This finding suggests that respondents who experience greater emotional intensity tend to perceive hypothetical evacuation scenarios as more urgent. At first glance this may seem to demonstrate that the descriptive scenarios were successful in eliciting a realistic emotional response from respondents. However, it is possible that respondents who reported greater emotional intensity also reported greater perceived urgency due to a desire to fulfill expectations. This is an example of social desirability bias, which could be controlled for in future work through the inclusion of a 33-item Marlowe-Crowne Social Desirability Scale [140].

4.2. External context

External context considers scenario-specific factors of the evacuation event. Parameter estimates for the random parameter logit model are summarized in Table 3, while marginal effects of the parameters and interactions are visualized in Fig. 3. Average marginal effects are reported to compare the relative influence of each variable in the model [141]. The adjusted rho-square of the model is 0.528. All parameters are statistically significant with a confidence interval of 97% or greater.

The stochastic component of the model can be interpreted using the standard deviation of the random coefficient. This random term was assigned to the ridesourcing utility function to account for unobserved heterogeneity across respondents by allowing the variance of the intercept to be individual-specific. The standard deviation of the random coefficient is relatively small at 1.56 and significant with a *t*-test result of 6.96. The ratio of the stochastic to systematic components of the random coefficient (i.e., $\alpha_{i,Ridesource}$ / $ASC_{Ridesource}$) gives the coefficient of variation of 0.287, which being small signifies low variance in the preference for ridesourcing across respondents. This is encouraging, because it suggests that the choice to use ridesourcing to evacuate was not made randomly. However, the fact that it is significant implies that respondents did experience more uncertainty with regard to this alternative, perhaps due to the somewhat hypothetical nature of using ridesourcing for evacuation.

Findings show that for small-scale evacuation events in the three most populous urban cities of the U.S., established modes are preferred to both ridesourcing and a combination of ridesourcing with established modes. Respondents also prefer using a combination of modes for evacuation compared to only using ridesourcing. However, the model reveals that ridesourcing is preferred by some socio-demographic groups in certain evacuation contexts. The remainder of this section focuses on specific external contextual factors and socio-demographic determinants of evacuation mode choice, summarized as three promising applications for ridesourcing, the results of which are presented in Table 4.

Table 3
Random parameter model results.

Name		estimate	*t*-test	p-value	marginal effects	
Alternatives						
	$ASC_{Established}$	0				
	$ASC_{MixedModes}$	4.26	14.90	0.00		
Random coefficient						
	$ASC_{Ridesource}$	−5.43	−13.97	0.00		
	$\alpha_{Ridesource}$	−1.56	−6.96	0.00		
Parameters						
Established	$\beta_{Under35}$	−1.53	−5.88	0.00	−0.267	
	$\beta_{Unfamiliar}$	−0.632	−4.18	0.00	−0.091	
Interactions						
Established	$\beta_{Far,Chicago}$	−0.660	−3.58	0.00	−0.085	
Ridesource	$\beta_{Severe,NewYork}$	0.991	2.82	0.00	0.009	
	$\beta_{Immediately,Chicago}$	0.958	3.17	0.00	0.008	
Mixed Modes	$\beta_{Black,LowIncome}$	1.82	2.16	0.03	0.097	
	$\beta_{LowIncome,Authority}$	1.65	5.44	0.00	0.075	
	$\beta_{Female,Nonwhite}$	1.03	4.45	0.00	0.032	
	$\beta_{Nonwhite,Friends}$	0.609	2.86	0.00	0.016	
Type of draws						Hess-Train
Number of draws (normally distributed)						1000
Number of observations						1479
Rho-square						0.536
Log likelihood at convergence						754.433

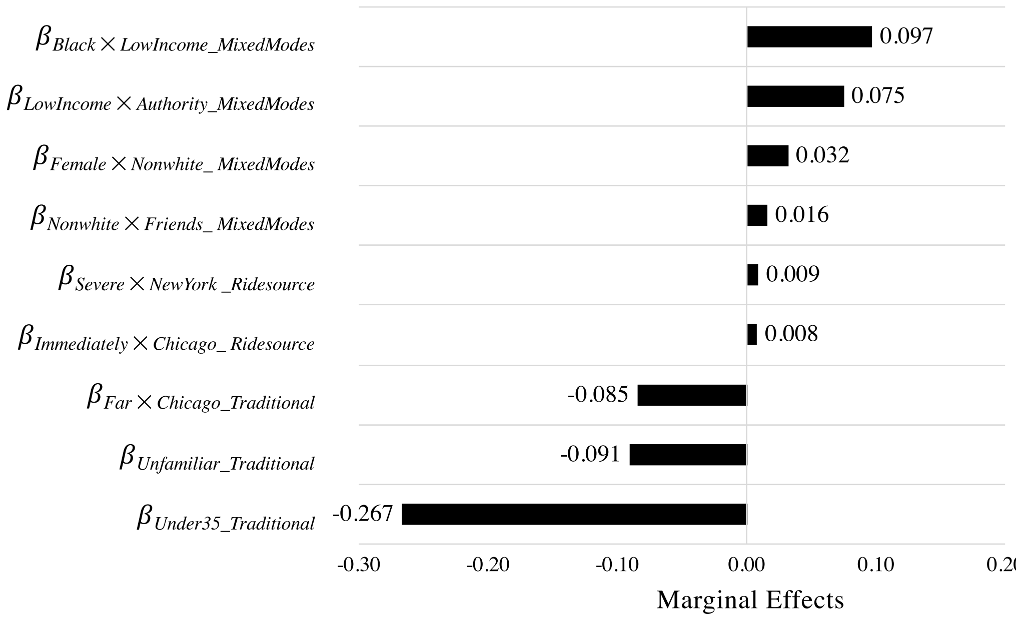

Fig. 3. Marginal effects for model parameters and interactions.

Table 4
Results for hypothesized applications.

A1: *Ridesourcing can fulfill a need for navigation during complete or partial evacuation*		
$\beta_{Under35}$	-	Established
$\beta_{Unfamiliar}$	-	Established
$\beta_{Far,Chicago}$	-	Established
A2: *Ridesourcing can fulfill urgency needs during complete evacuation*		
$\beta_{Severe,NewYork}$	+	Ridesourcing
$\beta_{Immediately,Chicago}$	+	Ridesourcing
A3: *Ridesourcing, as a partial evacuation strategy, can fulfill needs of vulnerable evacuees*		
$\beta_{Black,LowIncome}$	+	Mixed
$\beta_{LowIncome,Authority}$	+	Mixed
$\beta_{Female,Nonwhite}$	+	Mixed
$\beta_{Nonwhite,Friends}$	+	Mixed

4.2.1. Application 1: Ridesourcing can fulfill a need for navigation during complete or partial evacuation

The three main contextual factors under consideration for *Application 1* center on the factors that contribute to an aversion to established modes, namely being under the age of 35, being in an unfamiliar location, and having to travel a far distance. According to the marginal effects estimates, individuals who are under the age of 35 are 26.7% less likely to use established modes to evacuate, individuals evacuating from an unfamiliar location are 9.1% less likely to use established modes, and individuals evacuating a farther distance in Chicago are 8.5% less likely to use established modes. These three contexts exemplify cases in which the use of ridesourcing for partial or complete evacuation is strongly preferred to established modes.

These results call to mind the findings of Alemi et al. [142] that individuals who are more likely to use their smart phones for assistance with navigation are also more likely to use ridesourcing. Furthermore, they support the findings of Rayle et al. [7] that younger individuals are more likely to use ridesourcing under ordinary conditions. Ridesourcing was anticipated to be preferred when evacuating from an unfamiliar area, because individuals in this situation may have less knowledge of nearby transit stations and may feel more reliant on real-time route mapping. Younger individuals were also expected to have a greater preference for ridesourcing during an evacuation setting given their greater familiarity with the service during ordinary travel and potentially a greater need for navigation assistance due to frequent relocation during this stage in life.

In terms of partial evacuation, these findings may reveal a preference to use ridesourcing to evacuate only as far as a more familiar part of town or to the nearest transit station when the location is unknown, due to the on-demand, point-to-point services it provides. The Chicago-specific finding may suggest the presence of a convenient but not necessarily well-connected transit system, hinting at a possible gap-filling function of ridesourcing. Overall, these findings may have important implications for disruptions occurring near universities due to the higher density of younger individuals in these areas who are more likely to use ridesourcing and in parts of cities that are attractive to tourists and visitors due to the expected unfamiliarity of these individuals with the surrounding area which increases the likelihood of using ridesourcing for evacuation.

4.2.2. Application 2: Ridesourcing can fulfill urgency needs during complete evacuation

The two main contextual factors under consideration for *Application 2* as related to exclusive use of ridesourcing are consequence severity and immediacy. In New York, an evacuation event that presents severe consequences results in a 0.9% greater likelihood of using ridesourcing, and in Chicago, a requirement to evacuate immediately results in a 0.8% greater likelihood of using ridesourcing. These results are in line with the findings of Berger [143] that ridehailing companies, like Uber and Lyft, are often used in place of ambulances during medical emergencies.

These results reveal a demand for ridesourcing under life-threatening conditions, emphasizing the need to clarify rules and regulations for service use before the occurrence of such an event. Additionally, the scalability of these findings must be carefully examined given that only small-scale disruptions were considered. For example, the perceived rapidity of ridesourcing is observed to be an important determinant in Chicago, but during a large-scale evacuation, increased congestion likely would delay ridesourcing arrival, making it slower than established modes with priority lanes, such as an elevated train or subway. Overall, the effect sizes are weaker than for the other applications suggesting that there is a less pronounced role for complete evacuation via ridesourcing. Hence, more caution is warranted for exclusive use of on-demand mobility for emergency evacuation, prompting further study of issues related to affordability, effective coverage, and user trust.

4.2.3. Application 3: Ridesourcing, as a partial evacuation strategy, can fulfill needs of vulnerable evacuees

The six main contextual factors under consideration for *Application 3* are socio-demographic factors of race, gender, and class (i.e., Black, nonwhite, female, and low income), as well as the scenario-specific factors of an authority-issued evacuation mandate and traveling with friends. According to the model, when marginalized identities interact, ridesourcing can fulfill an evacuation need, but only partially. For example, Black individuals who are also low income are 9.7% more likely to use ridesourcing for partial evacuation, and females who are also nonwhite are 3.2% more likely to use ridesourcing for partial evacuation. Furthermore, disadvantaged populations may only be willing to use ridesourcing for partial evacuation under certain conditions. For example, when ordered to evacuate by a source of authority, low income individuals are 7.5% more likely to use ridesourcing for partial evacuation, and when evacuating with friends, nonwhite individuals are 1.6% more likely to use ridesourcing for partial evacuation.

The revealed significance of these interactions call to mind concepts of intersectionality theory [144], as based in feminist and critical race theory, which considers the experience of belonging simultaneously to multiple marginalized identities of race, gender, class, and sexuality. While the use of statistical interactions alone is not enough to capture the full extent of the possible multidimensionality of these identity interactions [145], the findings offer an initial suggestion of the complex role that identity plays in evacuation decision-making. To further explore this role in future work, additional survey questions will be applied to more accurately measure identity salience.

These results support the conclusions of Brown and Taylor [146] that ridesourcing offers a promise of increased mobility for disadvantaged communities but also a risk of exacerbating mobility inequalities [147]. For instance, research has shown that Black riders experience longer waiting times and more frequent cancellations by ridesourcing drivers [148]. It may be that individuals who are both Black and low income and individuals who are both female and nonwhite are aware of this potential discrimination, resulting in a minimal use of ridesourcing for evacuation. Low income individuals may use ridesourcing as a feeder mode when ordered by an authority to evacuate due to a lack of other available options, and nonwhite individuals may be more likely to use ridesourcing as a feeder mode when evacuating with friends possibly due to a decreased risk of having the ride cancelled if a friend hails the ride or an increased sense of safety or affordability while riding with others. These findings may have important implications for disruptions occurring in disadvantaged communities where gaps frequently exist in the transportation network.

5. Research implications

5.1. Debating the sharing economy

The debate surrounding the shared economy is centered on ethics, efficiency, and sustainability [149]. While there may be a tendency to interpret sourced rides from the crowd as altruistic acts of volunteerism, a volunteered action does not involve payment, coercion, or reward. Therefore, as companies and partnerships move toward establishing formal policies regarding crowdsourced evacuation rides, we must carefully consider the implications of encouraging or obligating sharing economy providers to perform such services. In the following, we limit our focus to three sharing economy concerns to initiate the evacuation ridesourcing debate.

The first major sharing economy concern is that it consists, at least in part, of for-profit companies (like Uber and Lyft) that are subject to financial motivation to behave in the economic self-interest of the company's owners and management. The second is that of labor exploitation. Some critics of the sharing economy have suggested that participation by employees in the sharing economy is not done out of a desire for social connectedness but rather out of economic need due to job shortages in an insecure economy [149]. In addition to a lack of alternative sources of income, critics have suggested that the sharing economy shifts risks from companies to their employees and provides services that can be unregulated and unsafe [149]. The third concern is that of unequal access to the sharing economy by low income and disadvantaged communities due to the requirement of smart mobile device access and expressions of discrimination based on race, gender, and class present on these platforms.

5.2. Public-private partnerships

One method for developing a pre-established protocol for providing evacuation ridesourcing is the formation of public-private partnerships between the government and ridehailing companies. Such partnerships have existed outside of the realm of disaster response, as in the former *Ride KC: Bridj*, a partnership between the former micro-transit company Bridj, Ford Motor Company, and the Kansas City Area Transit Authority [150]. Uber has also been involved in co-branded marketing campaigns involving short-term partnerships with transit agencies [151]. Public-private partnerships have the potential to develop multimodal transportation hubs in mobility disadvantaged communities [146]. However, the formation and maintenance of such partnerships is challenging due to both agency barriers and liabilities [152]. For example, transit agencies are required to guarantee equity protections to disadvantaged individuals under the Americans with Disabilities Act and Title VI of the Civil Rights Act, while ridehailing companies are not held to the same standards [151]. Furthermore, in providing evacuation services, ridehailing companies face liability risks. These companies may be sued by employees or their families in the case of death, injury, or damages incurred while providing evacuation rides, or by users of the services owing to drivers' actions during evacuation, [153].

To minimize liabilities, ridehailing companies should allow drivers who are interested in volunteering for this additional responsibility to register in advance and to receive emergency response training. These drivers should be held accountable through signed agreements with the company or sponsoring governmental agencies to reinforce follow-through, and drivers who participate in this program could receive a publicly-displayed honorary badge from the company [53]. While some liabilities may be reduced through user preregistration, driver training and credentialing, and careful supervision [11], many companies or individuals still may be unwilling to take on such risks.

5.3. Community-based non-profits

A second option for the formation of pre-established evacuation ridesourcing services is the development of community-based, non-profit organizations. The sharing of evacuation rides in this manner would be truly peer-to-peer by removing the service from the context of existing for-profit ridehailing companies. Examples of community-based, non-profit sharing economy services have been shown to increase trust and minimize the cost of long-distance transportation of services, such as in the case of tool libraries that have emerged in low income communities [149] or bicycle libraries, such as those promoted by the Bicycle Innovation Lab in Copenhagen [154] and Equiticity in Chicago [155]. To achieve such an arrangement, ridesourcing drivers would need to self-organize, replicate the software used by existing ridehailing companies, and achieve their own critical mass of users [149].

5.4. Contextually-tailored evacuation strategies

It is imperative that ridesourcing service providers have a disaster response plan in place before the occurrence of any emergency. If ridehailing companies decide to provide rides during an evacuation event, they must consider how to manage and regulate surge pricing, how much to subsidize drivers, and how to keep drivers fully-informed of the associated risks of providing rides during hazardous events.

For meeting navigational needs, the use of ridesourcing may not be necessary in all evacuation events, thereby incurring the consequence of increased traffic congestion without sufficient cause. Therefore, transportation planners may wish to shift users from spontaneous ridesourcing to public transit in order to increase efficiency. This could be done using hard measures, such as by placing a cap on the maximum allowed ridesourcing vehicles in the area, or using soft measures, such as tailored mobile phone notification strategies suggesting closer destinations, improving wayfinding signage, and offering community events or demonstration projects that familiarize residents with transportation options.

For meeting urgency needs, providing ridesourcing for evacuation could pose a serious threat to riders and drivers alike. Drivers may be requested to enter dangerous zones, and an increased level of stress and congestion may prevent efficient evacuation. Given these considerations, public-private partnerships may decide that the use of ridesourcing in this scenario should be discouraged. The use of soft measures to shift demand in these circumstances is also cautioned against due to the misleading nature of attempting to lessen the sense of severity or immediacy through tailored notification strategies.

In line with the findings from this research, ridesourcing should be used in tandem with existing services, in particular for vulnerable groups. Therefore, to meet needs of vulnerable evacuees, public-private partnerships should work to address equity challenges given that inequalities often worsen in times of crises. One option is to provide additional evacuation mode alternatives to transportation-limited individuals through the use of ridesourcing as a transit feeder mode. Governments should incentivize the sharing of these rides through subsidization. There are several potential strategies to boost incipient partnerships. Drivers should preregister to receive training and thorough background checks, and users should preregister to provide documentation of their specific transportation needs. Ridehailing companies should offer booking by telephone for those who do not have access to smartphones, as well as payment alternatives to credit or debit. For reasons of equity, ridesourcing drivers should be reserved specifically for this task rather than chiefly accepting riders who are willing to pay for an entire evacuation trip, which would provide greater profit to the driver and company. Additionally, drivers should be supplied in advance with necessary equipment to meet riders' needs, such as accommodations for child car seats, pets, oxygen tanks, luggage, etc. Finally, special care should be taken to address the potential discrimination of marginalized groups, such as by identifying drivers and riders by unique passcodes rather than by names, performing occasional behavior audits, and analyzing existing ridesourcing data [148].

5.5. Limitations and future work

This early investigation into the contextual determinants of evacuation ridesourcing is intended to provide initial guidelines for consideration of on-demand mobility for disaster response. However, this research presents some limitations that may be addressed in future work. First, in general, SP surveys incorporating highly hypothetical scenarios, especially those that inspire an emotionally charged state, are prone to response biases and reflect imagined reactions rather than real-world behaviors. For this reason, small-scale relocation events were considered as opposed to mass evacuations. Second, the choice experiment was focused on evacuation ridesourcing demand. Other research has provided evidence for driver willingness to supply evacuation rides, but these findings have relied upon declared data, which as mentioned may not truly reflect actualized behaviors. Before ridesourcing may be considered as a reasonable evacuation strategy, we must first thoroughly understand the motivations, incentives, and risk perceptions of drivers. Third, the choice experiment scenarios did not explicitly include common attributes of mode alternatives, such as time and cost. As a result, the choice model findings represent intrinsic preferences for one mode over another, but the reasons behind those preferences are left to interpretation. A future ridesourcing choice experiment including modal attributes is currently under development. Fourth, given the focus on small-scale urban evacuations with little or no notice, these findings cannot be directly extrapolated to more remote locations or to other evacuation scenarios, including hurricanes and wildfires. Finally, the consideration of emotionality as a fundamental trait, as applied in this study, was likely oversimplified at four questions aggregated across both positive and negative emotions. In future work, a distinction will be made between discrete emotional states with a focus on contextual relevancy. Future research is underway to develop a choice experiment that accounts for modal attributes and social influence. In this way, we will be able to measure scenario-specific and time-dependent impacts of mode alternative attributes, such as wait time, on evacuation decision-making. Additionally, the effects of receiver characteristics, such as social setting, social ties, and social structure, will be accounted for through social network data.

There are broader limitations of this research, as well, such as the need to address additional challenges presented by evacuation ridesourcing and potentially unforeseen negative consequences. Examples of unintended effects may include an increase in road network congestion, the prevention of emergency personnel from accessing a disaster area, and the incentivization of individuals to stay for too long in dangerous locations. Drivers may be physically hurt or killed in the process of trying to rescue others, or they may be overwhelmed by the emotional impact [156] and may experience long-term trauma. It is also uncertain how ridehailing companies may provide enough capacity to meet demand or how to prioritize rides in an equitable manner to fill existing gaps in the transportation network. However, it is clear from these findings that pre-established policies are needed to support collaborative disaster response enabled by innovative mobility services.

6. Conclusions

The recent increase in frequency and severity of weather-related disasters requiring evacuation has contributed to the worsening of infrastructure vulnerabilities worldwide. In the rapidly evolving context of the sharing economy and on-demand shared use mobility, it is important to understand how new services influence transportation use during emergencies to plan for resilient and equitable disaster response. While the effect of ridesourcing on evacuation behavior remains to be seen, this work provides an early glimpse into the contextual and sociodemographic factors affecting how these services might be used, when, and by whom in large urban cities across the U.S. Three applications of evacuation ridesourcing were considered to illustrate the effects of contextual differences on ridesourcing demand: (1) the fulfillment of navigational needs, (2) the fulfillment of urgency needs, and (3) the fulfillment of needs of vulnerable evacuees. On the whole, the model results reveal that there is no general acceptability of ridesourcing, rather the modeling reveals context-determinants (by city, as well as emergency communication and setting) and group-specific determinants. The consistent overlap between gender, income, and ethnicity suggests that overlapping identities, or intersectionality, is important to consider.

Based on the findings, provisions of context-dependent evacuation services are recommended. To shift demand between various evacuation modes, including the use of ridesourcing, soft strategies may include contextually-tailored emergency notifications. To prepare for adaptive evacuation response, whether through public-private partnerships or community-based non-profits, it is imperative to have policies in place ahead of any disaster event to protect drivers, passengers, and ridehailing companies alike. A caveat of the current research is the limited sample size that in turn constrained the exploration of complex internal contexts (i.e., identity and emotionality) and external contexts. Future work is planned to explore three main extensions, namely the inclusion of modal attributes such as reliability and cost, deeper exploration of the supply and contextual ridesourcing/transit environments in the study settings, and finally, the consideration of on-demand ridesourcing determinants for evacuation in rural areas to better understand the universality of these findings.

Declaration of interest

None.

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Appendix

Table 5
Eight scenarios capturing six factors of two levels each.

INSTRUCTIONS: "When responding to the following eight scenarios: If you would take multiple modes in sequence (such as walking to a bus stop and then riding a bus), please indicate (in this example, by selecting both 'Active transport' and 'Bus'). Assume your preferred mode is available."

Sociality	Familiarity	Source	Immediacy	Severity	Distance	
(low)	(high)	(low)	(high)	(low)	(low)	"It is early afternoon, and you are *alone* in your **office** when there is a sudden **blackout**. Someone comes to your door and *claims* that everyone must go home *immediately*. You live **2 miles away**. How do you get home?"
(high)	(high)	(low)	(high)	(high)	(high)	"You are in a **classroom** with *two friends* waiting for class to start when someone runs into the room and *claims* that a **bomb** has been reported on the premises and everyone must evacuate the area *immediately*. You and your friends live **10 miles** away. How do you get home?"
(high)	(high)	(high)	(low)	(high)	(low)	"You are with *two friends* in a *familiar* part of town when you receive an alert from a city official warning you that an accident involving a toxic tanker truck has released severely **hazardous material** into the surrounding area. You and your friends must evacuate within *30 min* and clear a **2-mile** radius. How do you evacuate?"
(low)	(low)	(high)	(high)	(high)	(low)	"You are running errands by *yourself* mid-morning on an *unfamiliar* block in your city when you receive a call from your child's school informing you that a **meningitis outbreak** has just been reported, and your child needs to be picked up *immediately*. No one else is available to pick up your child, and the school is **2 miles** away from where you are now. How do you reach your child?"
(high)	(low)	(low)	(low)	(low)	(low)	"You are with *two coworkers* attending a workshop at a **convention center** that you have *never* been to before in your city's downtown area. It is pouring rain, and you overhear someone *claim* that everyone should evacuate the area within the next *30 min* and clear a **2-mile** radius due to **severe flooding**. You and your coworkers agree to leave. What mode do you use?"
(low)	(high)	(high)	(low)	(low)	(high)	"You are reading *alone* at a university **library** when you receive an alert from the school's Emergency Management System warning everyone to go home within *30 min* due to increasing severity of a **blizzard**. You live **10 miles** away from the school. How do you get home?"
(low)	(low)	(low)	(low)	(high)	(high)	"You are participating in a **protest** without *anyone else* you know in an *unfamiliar* part of town. The protest is getting out of control. You hear a *rumor* that law enforcement personnel will start using **tear gas** if the crowd does not disperse within *30 min*. You decide to go home. You live **10 miles** away. How do you evacuate?"
(high)	(low)	(high)	(high)	(low)	(high)	"You are attending a **concert** with *two friends* in an *unfamiliar* part of town. It has just been announced that the final act has **cancelled** due to illness of the lead musician. Everyone is asked to leave the concert hall *now*, and ushers start to escort individuals outside. You and your friends decide to go back to your house, which is **10 miles** away. How do you get home?"

Table 6
Four attitudinal questions and four emotionality questions following choice experiment.

Attitudinal Statements					
"The sharing economy promotes environmentally-friendly consumption behavior, such as recycle-reuse-repurpose."	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
"Participating in sharing economies saves money."	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
"Participating in sharing economies improves my sense of community."	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
"I would recommend sharing economy services to my friends."	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
Emotionality					
"I say or do something I should not have done. I feel:"	Extremely guilty	Very guilty	Guilty	A twinge of guilt	It has little effect on me
"Someone compliments me. I feel:"	Ecstatic	Very pleased	Pleased	Mildly pleased	It has little effect on me
"I am trying to meet an important deadline and the tools I need are not working. I feel:"	So frustrated that my muscles knot up	Very frustrated	Frustrated	A little frustrated	It has little effect on me
"Someone I am very attracted to asks me out for coffee. I feel:"	Euphoric	Very thrilled	Thrilled	Mildly thrilled	It has little effect on me

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2019.101406.

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