Immersive Virtual Reality to Measure Flood Risk Perception in Urban Environments

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Abstract. About half of the world's population resides near coastlines, rivers, or inland streams. Climate change has led to more severe hydro-hazards (e.g., floods, storms) in these communities, causing significant economic damage and loss of life. Informed decision-making during flood evacuation, search and rescue, and sheltering depends on the availability of reliable information about the depth of floodwater in affected areas. While underestimating the water depth can be catastrophic, overestimating it may severely delay the deployment of goods and services. Our perception of risk and prior experience with floods influence how we interpret information to arrive at a decision. In this study, we utilize immersive virtual reality (VR) to reconstruct urban flood scenes and conduct a series of user studies to assess the human perception of flood risk on urban roads. This VR prototype is sought to improve human perception and communication of flood risks.

1. Introduction

Flood is the most frequent weather-related threat and the costliest natural hazard worldwide (Mizutori & Guha-Sapir, 2018). In the past 20 years, there have been nearly 5,000 flood events in the U.S., resulting in approximately 2,000 fatalities (American Climate, 2019). In 2021 alone, 223 flood events occurred in the world, which is higher than the reported annual average of 163 (Centre for Research on the Epidemiology of Disasters, 2022). Research points to asymmetric urbanization, growing coastal population, climate change, and deforestation as the main drivers of increased flooding worldwide (Bjorvatn, 2000; Sahin & Hall, 1996). Access to timely and accurate information is crucial in the aftermath of large-scale natural hazard events, such as floods and hurricanes. This information not only does support successful response and recovery (Gebrehiwot et al., 2019), but also aids in mitigation efforts and policymaking aimed at protecting people's health and safety, and reducing property or environmental damage (Federal Emergency Management Agency, 2016; Public Safety Canada, 2010).

Overlooking risk perception and communication, and public's concerns and needs can contribute to the failure of flood risk management practices (Bodoque et al., 2019). To ensure the success of flood risk management, it is imperative to consider the varying perceptions and understanding of flood risk and to effectively communicate this information to all stakeholders. Given the high cost and risks associated with collecting human data in the field in the aftermath of large-scale disasters, simulating a flooded region in a virtual reality (VR) environment can help mimic risks and consequences in a controlled lab experiment, and perform targeted investigation to quantify and potentially improve flood risk perception (Mol et al., 2022). Previous research has focused on how demographics affect risk perception, but there is little research on how immersive flood simulation can influence human perception of flood risk. The authors have previously created an application based on artificial intelligence (AI)-driven visual recognition to assist in estimating the depth of floodwater in real-time (Alizadeh & Behzadan, 2021; Alizadeh & Behzadan, 2022). This estimation is achieved by analyzing street-level photographs of standardized urban benchmarks, specifically traffic signs, using advanced convolutional neural networks. As an extension of this work, and in order to design a decision support tool for flood evacuation, it is critical to understand how people make decisions, and human's perception of risk is a driving decision-making factor in disaster settings (Botzen et al., 2009). In this paper, immersive VR is utilized to simulate a flooded urban environment to assess the human perception of flood risk.

2. Literature review

2.1 Flood risk perception

The risk assessment process involves the measurement of actual risk by experts, taking into account factors such as hazard, community exposure, vulnerability, and capacities (Aerts et al., 2018). On the other hand, the perceived risk is influenced by various factors, including exposure, prior experiences, community/individual understanding, cognitive thinking, and socio-political influences (Wachinger & Renn, 2010). Flood risk perception refers to the way in which individuals, communities, and organizations understand and respond to the risk of flood (Green et al., 1991). Perceptions of flood risk vary among people, potentially altering their exposure to risk. Considering this, disaster response and policymaking entities are paying increasing attention to the role of risk perception in order to navigate the development of new policies and technologies (Sjöberg, 2002). Previous studies have found a correlation between flood risk perception and socioeconomic factors including past flood experience (Botzen et al., 2009), age and gender (Babcicky & Seebauer, 2017; Siegrist & Gutscher, 2006), education and knowledge (Qasim et al., 2015), and income and occupation (Peacock et al., 2005). While previous research has predominantly examined the impact of demographics on risk perception, limited research has been conducted on investigating the influence of immersive flood evacuation environments on human perception of flood risk. Informed by these findings, in this paper, the impact of socioeconomic factors and urban landmarks on flood risk perception is studied.

2.2 Simulation of a disaster event in VR

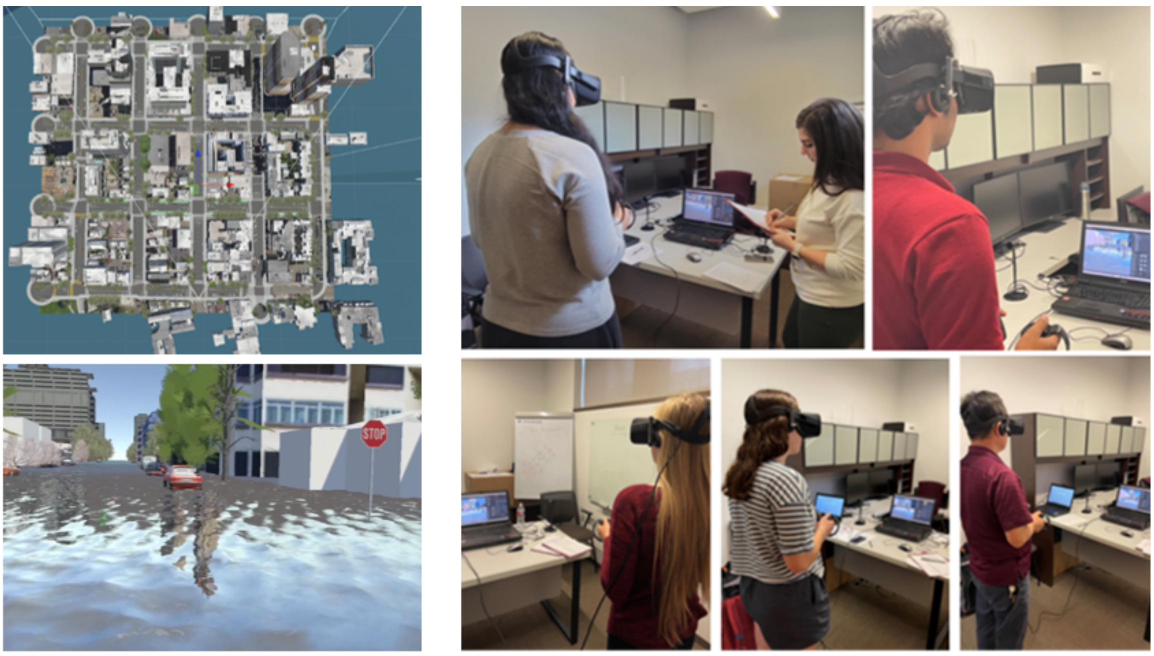
By creating a simulated environment that accurately replicates the experience of being present in a flooded area, VR can provide a safe and controlled space for individuals to develop an elevated understanding of associated challenges and risks. Unlike traditional tabletop experiments, through immersing individuals in a realistic flood scenario, VR can also help communicate the severity of the situation and increase awareness of the potential consequences of flood-related hazards. In recent years, VR and simulation technologies have been used to improve disaster preparedness and response. For example, Ooi et al. (2019) developed a VR-based educational training system focusing on fire disasters and concluded that participants' fire extinguishing start time was reduced by 10 seconds using this system. Ryu et al. (2007) developed a real-disaster video by combining real-time physical simulation and VR to provide a trial training for users in case of fire disaster. Aizhu et al. (2016) developed a VR training system for providing an evacuation experience in fire events. Xi and Smith (2014) enhanced the realism of VR-based fire evacuation training using gaming technology. Sermet and Demir (2019) developed a multi-player, voice-enabled VR gaming framework (called Flood Action VR) to improve flood risk awareness. Mol et al. (2022) utilized immersive VR to explore whether exposure to a simulated disaster can motivate individuals to invest in flood risk reduction measures and found that participants who experienced a virtual flood, invested significantly more in a designed flood risk investment game.

In conclusion, risk assessment is a crucial process that involves measuring actual risk by experts, while the perceived risk is influenced by various factors. Flood risk perception is an important aspect of risk assessment as it reflects on a person's awareness and comprehension of environmental risks, and explains how he or she chooses to be exposed to a particular risk. Previous research has investigated the potential of immersive VR simulation in improving disaster preparedness and response via indicators such as disaster consciousness and risk awareness (Mol et al. 2022). This works utilizes a series of human subjects experiments to examine whether immersive VR experiments that reconstruct urban flood scenes can help assess human perception of flood risk and provide new insights that could inform the development of new policies and technologies in this field.

3. Methodology

3.1 VR Environment

The virtual environment consists of a 3-by-5 block real scale 3D city, generated in ArcGIS CityEngine 2021. The model is imported into Unity to develop an immersive VR. The operation and physics in the VR environment are developed using the C# programming language. An Oculus Rift headset, with a resolution of 1280×800 (16:10 aspect ratio) and a 110° diagonal field of view, and built-in headphones and controllers are used to interface with the VR environment. To maximize user's sense of immersion, a simulated water body element (with user-managed height to model various flood depths) is added to the environment, and a flowing water noise is played in the background through the Oculus Rift headphones. The computing platform used to run the model is a laptop computer with an Intel i9 processor, 32GB of RAM, and a GeForce GTX 1080 graphics card. In the VR scene, five types of common urban landmarks (i.e., cars, buildings, stop signs, fire hydrants, and trees) are also simulated and placed in various locations. Figure 1(a) presents a screenshot of the top-view and first-person view of the VR environment using the VR headset.



(a) (b)

Figure 1: (a) Top-view and first-person view (as seen through the VR headset) of the VR environment (b) participants in the VR experiment.

3.2 Participants

Participants were recruited from Texas A&M University using university-wide emails and advertisements. The recruitment criteria restricted participation to respondents who were 18 years of age or older. In total, from the 66 people who expressed initial interest, 51 participated in the study. Data collection in the lab started on February 2023, and the last participant was scheduled for a session on early April 2023. On the day of the session, each participant completed all three parts of the study (i.e., taking a pre-survey, conducting the VR experiment, and taking a post-survey).

3.3 Procedure

The study protocol was approved by the Institutional Review Board (IRB) of Texas A&M University. All surveys and lab experiments were conducted on Texas A&M University campus. At the beginning of the study, participants were asked to fill out a pre-survey, with information about their age, gender, ethnicity, and past flood experience (if any). Upon the completion of the pre-survey, a 5-minute VR experiment was conducted, where each participant used the Oculus Rift headset and hand controllers to navigate (i.e., virtually walk) in the VR environment and explore their surrounding areas, as shown in Figure 1(b).

During the VR experiment, the participant was asked (at random locations) to stop and report his or her estimate of water depth at that location. The study personnel then logged the reported water depth and its corresponding location on the map in a data collection sheet. To arrive at this estimate, participants were instructed to obtain visual cues from any of the five urban landmarks of their choosing visible in the environment (i.e., cars, buildings, stop signs, fire hydrants, trees). Upon the conclusion of the VR experiment, the study personnel announced the end of the experiment and helped the participant remove the VR headset and controllers. The participant was then asked to fill out a post-survey, in which they ranked each of the five urban landmarks based on their visibility in the environment on a 5-point Likert scale (with score 1 indicating the least visible, and score 5 indicating the most visible) as well as the frequency by which they had used that object a benchmark to guide them in estimating the water depth (with score 1 indicating the least frequently used, and score 5 indicating the most frequently used).

4. Implementation and results

Pre-survey results indicated that the age of participants ranged from 18 to 62 years, with 43.14% under or equal to 25 years old, and 56.86% above 25 years old. Gender distribution was almost equal among participants, with 43.14% female and 54.90% male (1.96% did not disclose their gender). In terms of ethnicity, 43.14% of participants identified as White or Caucasian, 5.88% as Black or African American, 43.14%, as Asian or Pacific Islander, 3.92% as multiple ethnicities or other, and 3.92% did not disclose their ethnicity. Only 25.49% of participants reported prior first-hand experience with flood events, while the majority (72.55%) had no prior experience, and 1.96% did not remember. Based on the results of the post-survey, on a 5-point Likert scale, cars received the highest average recognizability score of 4.45 by all participants. Next on the list were stop signs (average score of 3.37), buildings (average score of 2.90), trees (average score of 2.55), and fire hydrants (average score of 1.73). The same survey also revealed that participants most frequently used cars as a benchmark to estimate flood depth (average usability score of 4.61) likely due to their omnipresence and participants' familiarity with their overall shapes and sizes. Stop signs were the second most utilized object (average score of 3.22), likely because they were also highly noticeable in participants' surroundings. In contrast, fire hydrants were the least frequently used objects (average score of 1.96) primarily due to their limited visibility in highly flooded areas. Table 1 presents the recognizability and the frequency of use of the five urban landmarks, as rated by the participants.

Table 1: Average recognizability and usability scores of various urban landmarks on a 5-point Likert scale, based on post-survey results.

Object	Car	Stop sign	Fire hydrant	Building	Tree
Most recognized	4.45	3.37	1.73	2.90	2.55
Most used	4.61	3.22	1.96	2.57	2.65

For each participant, the water level at the center point of the virtual scene was randomly selected between 50 cm and 150 cm. The average flood depth estimation error (FDEE) for each participant was then calculated as the average of difference between ground-truth flood depth and estimated flood depth, which was logged in the range of -83.33 cm and +70.56 cm, with an average of 9.09 cm. Using this convention, a positive FDEE value was considered underestimation while a negative FDEE value referred to overestimation.

Analysis of collected data showed that participants under or exactly at the age of 25 years achieved a mean FDEE of 6.87 cm (2.70 in.) while this value for participants above the age of 25 years was 10.77 cm (4.24 in.). With respect to gender, the mean FDEE was 6.88 cm (2.71 in.) and 12.56 cm (4.94 in.) for male and female participants, respectively. Also, analysis indicates that the mean FDEE for White or Caucasian participants was 4.71 cm (1.85 in.), for Black or African American participants was -30.45 cm (-11.99 in.), for Asian or Pacific Islander participants was 19.55 cm (7.70 in.), and for Multiethnicity or Other participants was 18.75 cm (7.38 in.). Moreover, the mean FDEE based on the most used object was 11.80 cm (4.65 in.) for cars, -2.84 cm (-1.12 in.) for stop signs, 17.46 cm (6.87 in.) for buildings, and -20.41 cm (-8.04 in.) for fire hydrants. With respect to past flood experience, the mean FDEE was 8.64 cm (3.40 in.) and 9.85 cm (3.88 in.) for participants with and without past flood experience, respectively. Also, the mean FDEE for those who participated in the VR experiment with a low water level at the center point (less than 1 meter) was 6.04 cm (2.38 in.), and for those with a high water level (more than 1 meter) was 11.79 cm (4.64 in.).

A second round of statistical analysis was conducted in SPSS to assess if there is a statistically significant difference in FDEE mean and standard deviation (indicator of the degree of variability) between different groups of participants with respect to the independent variables (IVs) of age, gender, ethnicity, past flood experience, the most used object (to estimate flood depth), and average flood level. Firstly, the Shapiro-Wilk test was performed on both dependent variables (mean FDEE and standard deviation of FDEE) with results indicating that both variables are normally distributed ($p = 0.377$, and $p = 0.180$ respectively). Next, t-test (for comparing two independent variables) and ANOVA tests (for comparing multiple independent variables) were performed. Further analysis within each group was conducted with respect to two subgroups of overestimators ($n = 30$) and underestimators ($n = 21$). In this context, over-estimators mostly overestimated flood depth (more than half of their estimates were greater than the ground truth flood depths), and under-estimator mostly underestimated flood depth (more than half of their estimate were less than the ground truth flood depths). To achieve better data balance, participants who had an equal number of overestimation and underestimation were grouped as underestimators.

Table 2 and Table 3 summarize the results of the statistical tests performed for all participants, and for each of the subgroups of underestimators and overestimators, respectively. According to the results, at 95% confidence level ($\alpha = 0.05$), no significant difference ($p = 0.325$) was found in mean FDEE for participants under or exactly at the age of 25 years (mean = 6.87 cm, SD = 33.40 cm) and participants above the age of 25 years (mean = 10.77 cm, SD = 27.62 cm). Also, no significant difference (p = 0.258) was observed in mean FDEE for male (mean = 6.88 cm, SD = 33.12) and female (mean = 12.56 cm, SD = 26.52 cm) participants. Also, according to the results, no significant difference (p = 0.452) was found in mean FDEE for participants with no flood experience (mean = 8.64 cm, SD = 33.28 cm) and participants with past flood experience (mean = 9.85 cm, SD = 20.55 cm). Among different most used objects to estimate water depth, no significant difference (p = 0.254) was observed in mean FDEE obtained using cars (mean = 11.80 cm, SD = 30.09 cm), stop signs (mean = -2.84 cm, SD = 15.29 cm), buildings (mean = 17.46 cm, SD = 16.51 cm), and fire hydrants (mean = -20.41 cm, SD = 43.76 cm). Furthermore, no significant difference (p = 0.250) was found in mean FDEE for participants with average water level less than 1 meter (mean = 6.04 cm, SD = 35.98 cm) and participants with average water level more than 1 meter (mean = 11.79 cm, SD = 23.85 cm).

Table 2: Statistical significance of FDEE mean and standard deviation with respect to independent variables (* $p < 0.05$).

Test	**IV**	**Groups**	**N**	**Significance (One-sided)**	
				Ave. FDEE	**St dev. FDEE**
t-test	Age	<= 25	22	0.325	0.494
		> 25	29		
t-test	Gender	Male	28	0.258	0.053
		Female	22		
ANOVA test	Ethnicity	White or Caucasian	22	0.034*	0.048*
		Black or African American	3		
		Asian or Pacific Islander	22		
		Multiethnicity or Other	2		
t-test	Past flood experience	No	37	0.452	0.151
		Yes	13		
ANOVA test	Most used object	Car	41	0.254	0.489
		Stop sign	4		
		Building	3		
		Fire hydrant	3		
ANOVA test	Average flood level	<= 1 m (39.39 in.)	24	0.250	0.089
		> 1 m (39.39 in.)	27		

However, at 95% confidence level (α = 0.05), there is a significant difference (p = 0.034) in mean FDEE among ethnicity groups, e.g., White or Caucasian (mean = 4.71 cm, SD = 31.13 cm), Black or African American (mean = -30.45 cm, SD = 27.11 cm), Asian or Pacific Islander (mean = 19.55 cm, SD = 25.40 cm), and Multiethnicity or Other (mean = 18.75 cm, SD = 35.94 cm). Also, there is a significant difference (p = 0.048) in FDEE standard deviation between ethnicity groups, e.g., White or Caucasian (mean = 29.57 cm, SD = 10.16 cm), Black or African American (mean = 50.81 cm, SD = 11.14 cm), Asian or Pacific Islander (mean = 30.17 cm, SD = 13.94 cm), and Multiethnicity or Other (mean = 31.41 cm, SD = 0.045 cm). This finding implies that individuals from different ethnic backgrounds may perceive flood risk differently which has been also reported in past literature (Babcicky & Seebauer, 2017). Specifically, Black or African American participants had significantly larger mean FDEE compared to Asian or Pacific Islander participants (p = 0.007), and had significantly higher degree of variability (quantified by FDEE standard deviation) in their risk perception compared to White or Caucasian participants (p = 0.006), and Asian or Pacific Islander participants (p = 0.008).

Table 3: Statistical significance of FDEE mean and standard deviation with respect to independent variables in two groups of overestimators and underestimators (* p < 0.05).

Test	**IV**	**Groups**	**N**	**Significance (One sided) (Underestimators)**		**N**	**Significance (One sided) (Overestimators)**	
				Ave. FDEE	**St dev. FDEE**		**Ave. FDEE**	**St dev. FDEE**
t-test/ Mann-Whitney test	Age	<= 25	10	0.351	0.494	12	0.387	0.816
		> 25	11			18		
t-test/ Mann-Whitney test	Gender	Male	11	0.041*	0.053	17	0.376	0.101
		Female	10			12		
ANOVA test/Kruskal Wallis test	Ethnicity	White or Caucasian	11	0.668	0.048*	11	0.604	0.599
		Black or African American	3			0		
		Asian or Pacific Islander	6			16		
		Multiethnicity or Other	1			1		
t-test/ Mann-Whitney test	Past flood exp.	No	15	0.063	0.151	22	0.373	0.221
		Yes	6			7		
ANOVA test/Kruskal Wallis test	Most used object	Car	15	0.240	0.071	26	0.696	0.140
		Stop sign	3			1		
		Building	1			2		
		Fire hydrant	2			1		
ANOVA test/Kruskal Wallis test	Ave. flood level	<= 1 m (39.39 in.)	13	0.056	0.089	11	0.114	0.970
		> 1 m (39.39 in.)	17			10		

Next, the Shapiro-Wilk test results reported that both dependent variables (mean FDEE and standard deviation of FDEE) in the subgroup of underestimators are normally distributed (p = 0.055, and p = 0.967 respectively). On the other hand, in the subgroup of overestimators the distribution of mean FDEE is normal (p = 0.729), however, the distribution of standard deviation of FDEE is not normal (p = 0.043). For non-normal distribution, Mann-Whitney test (for two independent variables) and Kruskal Wallis test (for multiple independent variables) were performed. Among White or Caucasian participants, overestimators (n = 11) achieved a mean FDEE of 27.84 cm, while this value for underestimators (n = 11) was -18.42 cm.

Meanwhile, all Black or African American participants (n = 3) underestimated flood depth with a mean FDEE of -30.45 cm. Among Asian or Pacific Islander participants, overestimators (n = 16) achieved a mean FDEE of 31.03 cm, while underestimators (n = 6) was -11.07 cm. In the Multiethnicity or Other group, the overestimator (n = 1) achieved a mean FDEE of 44.16 cm, while this value for the underestimator (n = 1) was -6.66 cm. However, given the sample size of this last group, extra caution should be exercised when interpreting these results. Research cites that the disproportionate impacts of flooding on marginalized communities (such as Black or African American population groups) may lead to mistrust and a different perception of risk within those communities. Also, since a large portion of communities who live in or near flood-prone areas consist of Black or African American residents, it is likely that this population group may perceive floods as a normal life event, thus moderating their risk perception. This normalization might stem from growing up in flood-prone regions and witnessing floods regularly. On the other hand, communities that have experienced floods in the past may have developed collective resilience and coping mechanisms which can contribute to a sense of confidence and lower perceived risk (Botzen et al., 2009)

Meanwhile, further analysis revealed that underestimator males (n = 11, mean = -25.68 cm, SD = 23.90 cm) made significantly (p = 0.041) larger FDEE compared to their female counterparts (n = 10, mean = -8.46 cm, SD = 18.25 cm). On the other hand, no significant difference (p = 0.376) was found in average FDEE among male overestimators (n = 17, mean = 27.95 cm, SD = 17.12 cm) and female overestimators (n = 12, mean = 30.07 cm, SD = 18.27 cm). While the sample size may be relatively small, these preliminary findings seem to (at least partially) support existing literature indicating that on average, females tend to worry about natural hazards more than males do (O'Neill, 2016).

5. Summary and Conclusion

In their previous work, the authors developed deep convolutional neural networks along with an application to support the ad-hoc estimation of floodwater depth by analyzing street-level photos of standardized urban benchmarks (i.e., traffic signs). This paper built upon that work by implementing immersive VR to simulate a flooded environment for assessing human perception of flood risk and evaluating how sociodemographic factors could potentially influence the perception of flood risk. Participants were asked to fill out two surveys and complete a 5-minute VR experiment in which they walked in a virtual flooded scene and estimated flood depth at random locations using benchmarking objects visible in the environment including cars, stop signs, buildings, fire hydrants, and trees. The objective of the VR experiment was twofold: (a) to identify the primary benchmarking object used by participants to estimate flood depth, and second, and (b) to examine the impact of various factors on flood risk perception during the evacuation process. Findings revealed that most participants used cars as their primary benchmarking object. However, in real-world settings, using cars as a benchmarking object may not be the best option since cars may not be readily visible in all places, their sizes may vary, and they can easily float away in floodwater. Further statistical analysis found no significant difference (p = 0.254) in mean FDEE when using different objects to estimate flood depth. These findings suggest that visually estimating the flood depth using a benchmarking object alone may not be sufficient, thus highlighting the need for designing a reliable and accurate tool to support decision-making in floods. The analysis also revealed a significant difference in mean FDEE and the degree of variability (FDEE standard deviation) among different ethnicity groups (p = 0.034, p = 0.048). Specifically, Black or African American individuals had higher mean FDEE compared to Asian or Pacific Islander individuals (p = 0.007), and higher FDEE variability compared to White or Caucasian (p =

0.006) and Asian or Pacific Islander individuals ($p = 0.008$). A potential future direction of this research will involve a larger and more diverse sample of participants outside of university settings to better assess the impact of sociodemographic, vulnerability, and individual factors on flood risk perception, and provide more accurate insights into how different population groups may understand, communicate, and respond to such risk in the real world.

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