Investigating the Feasibility of Using Virtual Reality to Study Human Response to Flood Risk in 3D Flood Simulation

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Abstract

Mortality during floods is often related to human actions and perception of risk during emergencies. However, the lack of real-world data makes it difficult to study how people make decisions and act. Virtual reality (VR) offers a solution by simulating flood scenarios in controlled settings, enabling a deeper understanding of human risk perception and actions. Taking advantage of VR, this study designs a game-like flood event by simulating the continuously rising water on the street in the Unity 3D game engine, and aims to study how human responses vary when human are walking on the street or sitting in the driver's seat under different conditions of rain level ("normal" or "heavy"), illumination ("day" or "night"), and warning ("warning notification" or "no warning"). Also, learning from protection motivation theory (PMT), this study aims to investigate how people's perception of flood risk and their belief in self-protection during preparedness affect their decision making for exiting a flood emergency. Results from 50 participants show that: 1) Females exhibit longer response times and greater tolerance for flood risk compared to males; 2)Risk recognition takes less time when people are in the car than on the street; 3) ANOVA results show significant differences in response times between "day" and "night" conditions, and between "no warning" and "warning notification" scenarios; 4) Linear mixed-effects models suggest that higher confidence in self-protection efficiency correlates positively with earlier Flood risk recognition; 5) Higher levels of education and income may be associated with faster risk recognition and evacuation in the event of flooding. These findings highlight the variability in human perception based on different contextual factors, such as rain level, illumination and warning. Finally, the paper also discusses limitations and future research. Overall, this paper highlights the potential of VR simulations to enhance public understanding of Flood risks, promote awareness, and improve decision making in emergency contexts.

Keywords: Game-based flood experience, flood preparedness, disaster response, disaster resilience psychology, human-machine interaction

1 Introduction

As indicated by the National Weather Service (NWS) Preliminary United States Flood Fatality Statistics [1], there were 146 fatalities attributed to flooding in 2021, and nearly 80% of these fatalities occurred in vehicles or homes. Furthermore, the number of deaths reached 182 in 2024, with nearly 50% involving people over 60 years of age. The increase in flood deaths can be attributed to two primary factors. First, the vulnerability of aging urban systems may not adequately protect the safety of individuals and their property, which also exacerbates climate anxiety in cities (Mol et al., 2023; Cobbinah, 2021; Ogunbode et al., 2022; Negri et al., 2025c). Second, individuals often remain unaware of flood warnings and are hesitant to evacuate even in the face of immediate danger (Sorensen and Mileti, 1988; Osberghaus et al., 2025; Bamberg et al., 2017). However, in comparison to the first factor, understanding human responses is much more challenging due to the limited availability of empirical data on human behavior during flood emergencies.

[1]NWS Preliminary US Flood Fatality Statistics are available here: https://www.weather.gov/arx/usflood

Previous studies have shown that human preparedness and responses during floods significantly impact the results of these events, such as flood losses (Haer et al., 2016; Sivapalan et al., 2012; Alonso Vicario et al., 2020; Parker et al., 2009). For instance, Parker et al. (2009) found that the public does not act appropriately during floods, possibly because people have less understanding of the risk of floods, how to access and confirm flood warnings and how to respond actively and so on, which influences the severity of the consequences. Thus, a deep understanding of human behaviors and responses is essential for effective flood risk management and mitigation strategies. Research by Grothmann and Reusswig (2006) has shown that the socio-psychological model based on protection motivation theory (PMT) can explain why some residents take action while others do not perceive their risk of flooding, which also implies that more public risk communication efforts and effective training of early evacuation decisions can help residents with self-protective behavior (Peden et al., 2023; Hirunsalee and Kanegae, 2012).

Currently, most studies on evacuation decisions rely on surveys, questionnaires, and video training to examine human behavior and the determinants of these decisions. However, many people have limited experience with severe floods, making it difficult for those who have never faced such threats to fully comprehend the potential severity (Siegrist and Gutscher, 2008). Moreover, current methods have limitations in revealing how and when individual actions occur in real world scenarios (Drury et al., 2013). Therefore, leveraging emerging technologies to explore new effective methodologies to understand individuals' perceptions, responses, and actions about flood risk is paramount to developing emergency strategies and policies aimed at improving public awareness and preparedness.

Several researchers have begun to investigate the use of virtual reality to simulate disaster scenarios (Alene et al., 2023). This approach allows users to interact with these situations in an immersive environment. For instance, VR has been employed to assess public policies for flash flood evacuation and to assess flood risk management in sponge cities, illustrating the advantages of VR for risk communication (D'Amico et al., 2023a; Aahlaad et al., 2021; Fujimi and Fujimura, 2020). The benefits of VR include the establishment of a feedback loop between environmental adaptations and human decision making, which can facilitate the prediction of potential human responses in various flooding scenarios.

However, VR-based studies on flood risk perception and evacuation behavior remain limited. Most existing research focuses primarily on flood simulation to evaluate flood severity, rather than analyzing human interactions to understand responses, as discussed in detail later in this paper. Consequently, this paper aims to develop an innovative game-like and user-centered experimental design to measure human responses to evacuation preparation in the face of urban flooding.

2 Related work

2.1 VR and Disaster Simulation at Human-scale

Disaster emergency management is imperative to protect human life and the environment against natural and man-made disasters (Kathleen Geale, 2012; Elkbuli et al., 2021). The literature indicates that the disaster management process can be categorized into four phases: mitigation (mainly in the pre-crisis), preparedness (mainly in the pre-crisis), response (during the crisis) and recovery (post-crisis) (Emanuele Lettieri, 2009). The response phase typically involves immediate action to save lives and minimize economic losses, yet a significant number of human casualties and losses still occur during this phase. Researchers highlight the importance of effective mitigation and advance preparedness in reducing human losses(Mallick et al., 2005; Farahani et al., 2020).

To reduce the impact of disasters on society, a variety of tools have been used, including real-time monitoring sensors (Negri et al., 2025a), agent-based modeling (ABM) (Mesta et al., 2024), Geographic Information System (GIS) and Building Information Modeling (BIM) (Amirebrahimi et al., 2015, 2016). Current research is concerned with vulnerability assessment (Aahlaad et al., 2021; Uno and Kashiyama, 2008), disaster resilience (Khanmohammadi et al., 2020), disaster preparedness (Qureshi et al., 2006), early warning systems (Li and Li, 2012; Arora and Ceferino, 2024) and post-disaster reconstruction of facilities (Ceferino et al., 2025; Negri et al., 2025b). In addition, mobile alerts (Yoder-Bontrager et al., 2017) and various evacuation simulation software (Yang et al., 2014) have been incorporated into a comprehensive disaster management strategy to enhance interaction with the public during emergencies.

These approaches offer different perspectives on topography, geography, morphology, and urban planning; however, most focus on systemic issues at the meso-level and the behavioral patterns of large urban populations, rather than addressing the specific needs of individuals in critical situations at micro-levels. As a result, current studies have yet to accurately understand and simulate the dynamics between environments and individuals at the human level.

Human-level environments, referred to as open public spaces at the micro-level of cities, such as parks, streets, and plazas, are closely linked to human safety and evacuation during disasters (Jayakody et al., 2018; Matos Silva and Costa, 2018). These aspects remain insufficiently explored. Thus, it is essential to investigate new tools and methods to integrate disaster management into urban spaces and tailor solutions to diverse scenarios through an effective examination of human-environment interactions.

Virtual reality, a computer-based environment design tool, simulates physical objects within scenes composed of virtual elements that allow users to interact with a virtual environment. Taking advantage of VR simulation, researchers can virtually manipulate various experimental factors that may be difficult to replicate in real life due to safety concerns or prohibitive costs (Skinner, 2020). This capability enhances the utility of virtual reality technology in disaster management applications, which have been explored in various fields over the past decade, including infrastructure assessment, public awareness, and disaster response training (Khanal et al., 2022; Wu et al., 2017; Zhu and Li, 2021; Sermet and Demir, 2019).

Moreover, the digitization and visualization capabilities of VR can facilitate the representation of real scenarios related to various disasters in the built environment (Zhu and Li, 2021). For example, VR has been used to simulate a range of hazards, including floods, fires, earthquakes, terrorist attacks, radiation, and thunderstorms. Research indicates that VR simulation and human-level training are more effective than non-interactive training methods, such as training videos, in terms of knowledge acquisition and improvement in self-efficacy (Zhu and Li, 2021; Lovreglio et al., 2021; Çakiroğlu and Gökoğlu, 2019). Furthermore, the application of VR across the three phases of disaster management has been investigated (Zhu and Li, 2021), leading to the development of practical tools (Alene et al., 2023; Skinner, 2020) and serious games for educational purposes (Skinner, 2020; D'Amico et al., 2023b).

2.2 Flood risk and Perception in VR

Virtual reality has been used in urban flood research in the past 20 years (Kelner et al., 2001; Dang et al., 2023; Wang et al., 2019). Especially in the last five years, an increasing number of studies have explored the interaction between the human environment and VR to better understand human behavior, perception, and well being (Sermet and Demir, 2019; Simpson et al., 2022a). This exploration serves to improve public participation and communication (Lai et al., 2011; Korani and Martinez, 2023) in flood preparedness, as VR has been recognized as an effective tool that could mitigate human mental stress (Sikka et al., 2019; Rizzo and Shilling, 2017).

Researchers also confirmed that VR flood simulations can also instill a sense of urgency among participants, as VR can represent immediate, dynamic, and continuous changes in floodwater, such as rising water levels during flash floods, rather than relying on static scenarios, which validate the effectiveness of VR in flash flood evacuation experiments (Fujimi and Fujimura, 2020; Bernardini et al., 2020; Simpson et al., 2022b; Skinner, 2020). Consequently, along with VR, many researchers are investigating the applications of augmented reality (AR), mixed reality (MR), extended reality (XR) and digital twin (DT) technologies (Tomkins and Lange, 2019; Haynes and Lange, 2016; Levy and Liu, 2022; Bakhtiari et al., 2024) to enhance immersive experience by blending simulation with the real world (Tomkins and Lange, 2019; Haynes and Lange, 2016; Levy and Liu, 2022; Bakhtiari et al., 2024).

In city-scale simulations, researchers use various data and tools, such as topographical and hydrological information, to simulate flood dynamics and forecast general trends for the near future (Lai et al., 2011; Denda and Fujikane, 2024). For example, Dang et al. used VR panoramic videos from UAVs and cellular automata - position-based dynamics (CA-PBD) to achieve multiscale fusion and flood visualization (Dang et al., 2023). In human-scale environments, researchers focus on designing human experiences, such as incorporating loud sound effects, and determining indicators related to human evacuation, such as human motion speed (Bernardini et al., 2020) and evacuation time (Fujimi and Fujimura, 2020), to better understand decision-making processes.

Risk perception is defined as the likelihood and severity of threats that individuals evaluate, encompassing the entire process of forming a risk judgment (Simpson et al., 2022b; Dash and Gladwin, 2007; Birkholz et al., 2014; Kates and Kasperson, 1983). Simpson et al. (2022) investigated the perceived flood risk of storm surges using a virtual reality simulation and developed a real-world elevation task to assess knowledge transfer from the simulation to real-world contexts (Simpson et al., 2022b). Fujimi and Fujimura (2020) developed a virtual city and river and analyzed the timing of evacuation decisions in different scenarios, including those with inadequate evacuation warnings, evacuation-promoting designs, and combined interventions (Fujimi and Fujimura, 2020). Bernardini et al. (2020) compared the speed of human movement in still water with different heights for evacuation (Bernardini et al., 2020) and found that the speed of human evacuation was significantly reduced when the water level exceeded 60 cm.

Although the benefits of using virtual reality to simulate floods and study human responses, behaviors, and perceptions of risk have been recognized, it is still in the early stages of exploring how to build human-environment interaction in flood simulation to study how human perceptions of risk and their belief in their self-protection abilities in preparedness are translated into actions to protect themselves.

2.3 Protection Motivation and Flooding

Protection motivation theory (PMT), developed by Rogers in 1975 and revised in 1983, provides a framework for understanding the effects of fear assessment and persuasive communication on protection motivation and behavior, with a focus on cognitive processes (Rogers, 1975; Rippetoe and Rogers, 1987). This theory examines "fear appeal", a mechanism through which individuals' negative emotional responses triggered by threat perceptions influence their processing of threat warnings and subsequent actions (Ruiter et al., 2014). The process encompasses two components: 1) threat appraisal, which evaluates the severity of the threat and personal vulnerability, including perceived vulnerability, perceived severity, and fear; and 2) coping appraisal is the combination of "response efficacy", which evaluates the individual's acceptance of the recommended action promoted by presented effectiveness, and "self-efficacy", which evaluates the individual's ability to implement those responses (Ruiter et al., 2014). Previous research indicated that threat appraisal is positively related to maladaptive coping, while coping appraisal is positively related to stronger protective motivation (Milne et al., 2000; Rippetoe and Rogers, 1987; Floyd et al., 2000). A National Household Survey conducted in 2021, which included 4,559 samples, examined the role of "response efficacy" and "self-efficacy" in the preparedness measures adopted by vulnerable households. It found that response efficacy is more critical for low-capacity families and those caring for older or disabled adults, while self-efficacy is more important for low-capacity families and those caring for children (Qiu et al., 2023).

An adapted PMT has been used to take into account additional factors in specific areas such as health-related behavior(Milne et al., 2000) and disaster preparedness (Tang and Feng, 2018). The study by Torsten Grothmann demonstrated that PMT can serve as an effective model to understand flood preparedness (Grothmann and Reusswig, 2006). He examined the socio-psychological adaptation model, which incorporates individuals' subjective perceptions of flood risk and their coping abilities. This study discovered that perceptual factors are more predictive of flood adaptation than socioeconomic factors (Grothmann and Reusswig, 2006). Banerski and Abramczuk (2023) used 3D animation to simulate flood risks, along with PMT, to evaluate the self-protective behaviors of people living in flash flood-prone areas in Poland (Banerski and Abramczuk, 2023). In addition, Bubeck et al. (2017) gathered information on PMT flood coping assessments from a survey of 1,600 flood-prone households in Germany and France, highlighting the positive influence of the social environment (e.g. friends, neighborhood) on flood coping assessments (Bubeck et al., 2018). However, a concerning finding of Leventhal et al. (1965) indicates that fear appeals do not translate into action in some situations (Leventhal et al., 1965; Ruiter et al., 2014), and current researchers are also critically examining the effectiveness of warning messages on response efficacy and self-efficacy (Sutton et al., 2021; Parker et al., 2018).

Many researchers have identified response efficacy and self-efficacy as critical factors in decision making (Newnham et al., 2017; Benight and Harper, 2002; Marceron and Rohrbeck, 2019); however, individuals' stated intentions do not always translate into actual behaviors, known as the behavior-intention gap (Osberghaus et al., 2025). For example, Bamberg et al. (2017) found that the assessment of threat and adaptation is significantly associated with preventive intentions and flood behaviors, but these factors only account 13% of the variance in the prediction of the adoption of adaptive behaviors and intentions of floods on average. Kuhlicke et al. (2020) highlighted that this gap emphasizes the need for new methodologies that go beyond self-reporting to improve the understanding and prediction of human responses in flood risk scenarios. Additionally, fewer studies have focused specifically on the context of disaster preparedness to understand people's overall appraisals of flooding and their beliefs in their coping abilities, and to investigate how these factors are associated with real-time actions during flooding events.

2.4 Study Objectives

Integrating with PMT theory, this study aims to design a simple game-like interaction in VR to study human decision making in the face of flood dynamics and to investigate the impact of various factors (e.g. fear, self-protection efficacy, and demographics) in the preparedness stage on human decision making during flood events. A key focus of this study is to assess the variability of human responses to flood risks based on contextual information.

This paper aims to: 1) assess the feasibility of using virtual reality to study human perception of flooding through human-environment interaction in urban public spaces; 2) compare and analyze variations in human responses with changes in contextual information; 3) investigate factors influencing human responses to risk by analyzing the relationship between human responses during floods and their general perceptions of danger, fear, and self-efficacy in preparation and other demographic characteristics.

3 Study Design

3.1 Flood simulation in Unity 3D

This study used the Unity 3D engine alongside pre-built and high-fidelity 3D models sourced from the Unity Asset Store [2] to simulate flooding. The assets included buildings, streets, and streetlights, providing users with a familiar virtual experience and functions as reference points to observe variations in flood depth. A critical aspect of enhancing the fidelity of the flooding simulation is reflection, specifically the reflection of light and images: 1) implementation of moving textures with varying reflection rates to amplify wave effects (light reflection); and 2) use of an underwater reflective camera that aligns symmetrically with the main camera (the user's perspective) positioned above the water surface.

Two illumination settings were established to represent day and night (Part A in Figure 1), complemented by a rain particle system and accompanying rain audio to simulate falling raindrops. To simulate rising water levels, a flat plane was utilized along with a bump mapping technique, which provides dynamic depth at different points, effectively mimicking a rippling water surface. For performance optimization, unnecessary lights were eliminated, ensuring that most did not cast shadows. Additionally, all non-moving models and lights were designated as static, and lighting effects were baked to reduce the lighting load.This study decreases prior to transitions. In addition, adjustments were made to the position, font, font size, and other details within the models to alleviate discomfort.

In this study, a Unity 3D program was implemented on the Oculus Quest 2, a virtual reality device developed by Meta, which is commonly utilized in contemporary research. Both Oculus and Unity provide packages for device position input, as well as video and audio output, facilitating the management of input from VR controller buttons. For example, users press the "Y" button to initiate rain and press the "Y" button again to submit their responses.

Three cameras were established to provide two distinct views (Part B in Figure 1): 1) the walk view, which allows users to move horizontally within the virtual environment; 2) the drive view, where users remain seated and can only observe their surroundings in the virtual worlds. Regardless of the user's gaze direction, information is consistently displayed at the same position relative to their view, as the user interface canvas is anchored in front of the camera. To account for the varying levels of 3D dizziness induced by movement with the VR controller (as opposed to movement in the real world), this study incorporated an interface within Unity 3D graphical user interface (GUI) to adjust movement speed.

3.2 Experiment Design

All participants participated in a VR-based study consisting of 32 trials under different conditions lasting 40 minutes. The experimental conditions included: 1) two types of illumination: day and night; 2) two levels of rain intensity: normal and heavy; 3) two types of warning message: no notification and alarm notification; 4) two perspectives: walking and driving. This study ultimately included up to sixteen different conditions (2 * 2 * 2 * 2), each repeated twice for consistency, for a total of 32 trials.

All trials were conducted automatically and randomly, but the participants first completed all the trials in the walk view (16 trials in total) before switching to the drive view (16 trials in total). With regard to

[2]website for searching asset for Unity: https://assetstore.unity.com/

Figure 1: Part A): Two illumination settings in Unity: the low illumination setting represents nighttime and the high illumination setting represents daytime. The left figures for both ‘nighttime’ and ‘daytime’ show the initial stage of flooding, while the right figures show the rise in water levels during the flood event. Part B): Two views experienced by the participants: The left figure under the “Walk" view shows the flooding that participants would experience while walking down the street, while the right figure under the “Drive" view illustrates the flooding as seen from the driver’s perspective.

the design of the warning messages, this research aims to evaluate whether precautionary approaches influence decision making: “no notification" means that participants receive no additional information and must rely solely on their visual perception; “alert notification" means that participants hear sirens when flooding occurs (i.e., when accumulated water on the ground reaches 6 inches).

In each trial, participants were instructed to press a button three times to report their perceptions of flooding, as shown in Figure 2: 1) when they noticed abnormal rain (“abnormal"); 2) when they felt vulnerable as their situation became dangerous and doubted their ability to protect themselves (“dangerous"); 3) when they felt hopeless and had to leave the game (“life threatening"). The participants would proceed to the next test immediately after pressing the button for the third time.

Before the virtual reality (VR) experiment, participants were required to read self-protection messages (Appendix B) provided by the investigator and complete a pre-experiment survey (Appendix A). The purpose of the pre-experiment survey was to assess participants’ awareness of flooding based on prior knowledge and experience in the preparedness stage, specifically: 1) their understanding of flood severity and risks, and 2) their assessment of evacuation measures and capabilities. This survey was offered to participants prior to the VR experiment. The self-protection messages used in this study were taken from the official government website and consisted of nine recommendations for pedestrians and eight for motorists to mitigate risks during flooding. Participants were not required to memorize the messages; instead, they rated the effectiveness of the self-protection methods presented and self-rated their ability to implement these methods during floods. The questions about flood risks, threats, fear, and self-protection in the pre-experiment survey were adapted from the study by Banerski et al. (2023) (Banerski and Abramczuk, 2023), which aimed to assess self-protection motivation in a simulated flood context.

This study has been approved by the ethics committee. In compliance with data privacy protection regulations, participants will be assigned a random number for identification purposes and will be instructed not to provide personal information on the survey or devices. Participants received $10 as compensation upon completion of their participation.

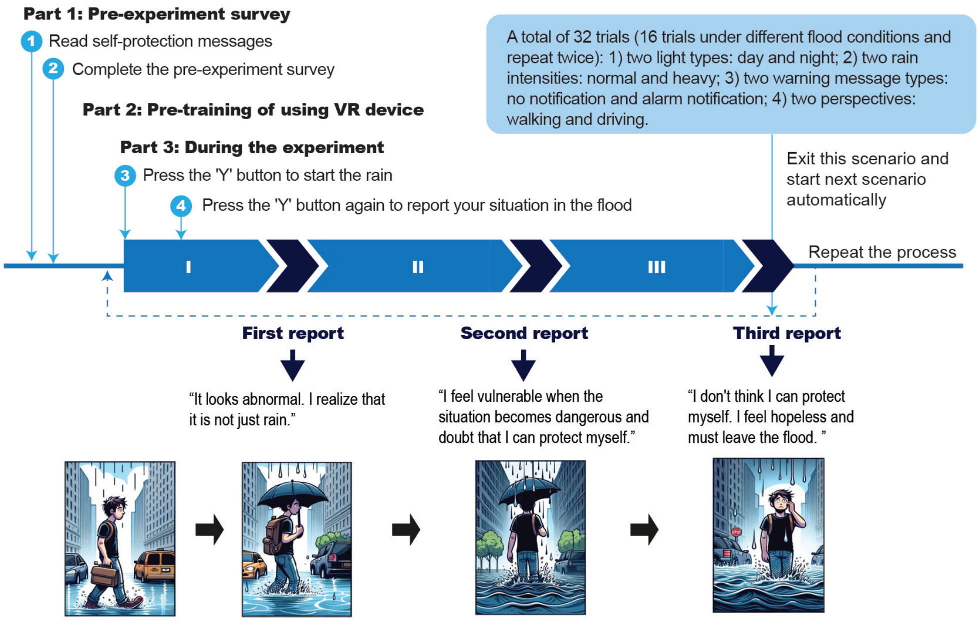

Figure 2: Experimental steps: 1) Participants completed the pre-experiment survey; 2) Participants followed the pre-training of using the VR device; 3) Participants entered the unit and press "Y" button to report three times based on their perception of Flood risks and repeat this process until the end of all trials.

3.3 Research data

The study recruited a total of 50 participants through university platforms, including email and student groups. The sample consisted of 28 males and 22 females, primarily graduate students. From the Table 1, most participants were aged 25-34 (50%) and 18-25 (36%). The survey indicated that over half of the participants had limited experience with flooding, reporting "never" (34%) or "rarely" (52.6%) experienced events, and self-assessed their knowledge of flooding as inadequate, with ratings of "Poor" (20%) or "Fair" (48%). Furthermore, most of the participants (82%) reported that they did not receive self-protection training during floods. The results of the PMT-related questions in the pre-experiment survey can be found in Appendix C.

Features	Categories	Number	Percentage
Gender	Male	28	56%
	Female	22	44%
Age	18-24 years old	18	36%
	25-34 years old	25	50%
	35-44 years old	6	12%
	65+ years old	1	2%
Education	Graduate or professional degree	33	66%
	Bachelor	14	28%
	College	3	6%
Income	Less than $25,000	9	18%
	25,000−49,999	14	28%
	50,000−74,999	5	10%
	75,000−99,999	7	14%
	100,000−149,999	4	8%
	Over than $150,000	4	8%
	Prefer not to say	7	14%
Long-time Health Condition	No	44	88%
	Yes	3	6%
	Prefer not to say	3	6%
Drive Ability	Yes but not often	30	60%
	Yes, often drive	13	26%
	No	7	14%
Flood experience	Frequently (Annually)	1	2%
	Occasionally (Every few years)	6	12%
	Rarely (Once or twice up to now)	26	52%
	Never	17	34%
Training	Yes	2	4%
	No	41	82%
	Not sure	7	14%
Flood knowledge	Very Good	1	2%
	Good	15	30%
	Fair	24	48%
	Poor	10	20%

Table 1: Summary of the characteristics of all the participants

3.4 Modeling Analysis

This study aims to analyze how self-protection motivation influences decision making in various flooding scenarios. Initially, as in our study, the same participants are measured multiple times under different conditions; therefore, we conducted a repeated measures ANOVA test to determine whether participants' responses (i.e., “first report", “second report", “third report") significantly vary based on changes in “rain level"(normal/heavy), “warning types" (no notification/alarm notification) and “illumination" (day/night). To further investigate human responses, we calculated the time intervals between the three responses: “threat confirmation" (between the second report and the first report), “motivation loss" (between the third report and the second report) and “risk tolerance" (between the third report and the first report), as illustrated in Figure 3. Log transformation was applied to the response time data in ANOVA and the following linear mixed-effects model to mitigate the effects of skewness and to approximate a normal distribution.

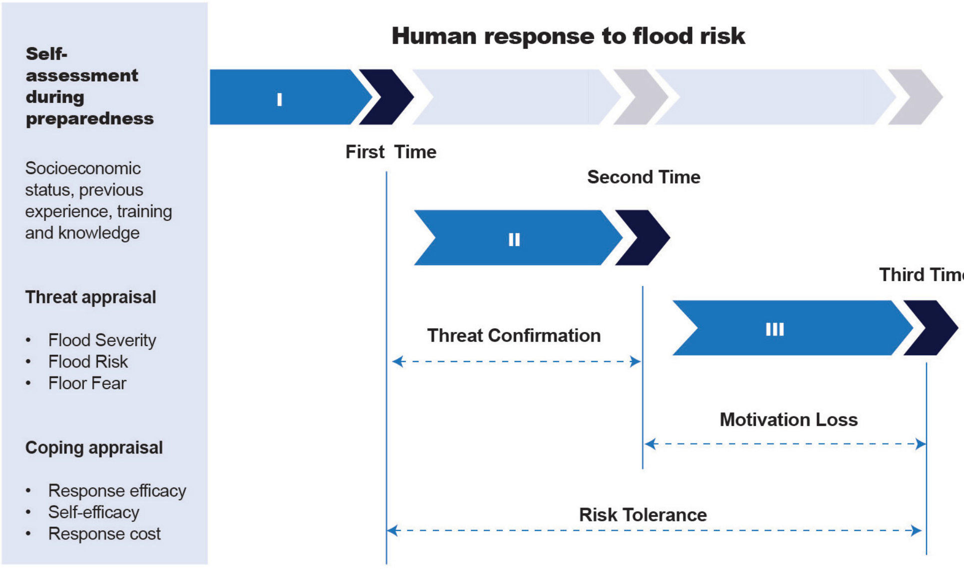

Figure 3: Various variables were measured at all stages: 1) from the pre-experiment survey, participants' socioeconomic status and previous experience were collected, self-assessment of threat appraisal and coping appraisal were assessed by PMT survey; 2) during the experiment, participants' reports were recorded three times, separately "first report", "second report", "third report"; 3) the duration between three reports was assessed to represent the time used for people's decision making, mainly focusing on "threat confirmation", "motivation loss" and "risk tolerance".

In this experiment, each of the 50 participants experienced eight types of conditions in two perspectives of "walking" and "driving" and was repeated twice. The average values of each response time for each of the eight conditions were calculated separately for the "walking" and "driving" perspectives. We can find the nested structure including both "users" and "conditions" existing in our database. Consequently, we employed linear mixed-effects models to assess the impact of self-protection motivation on participants' responses across varying conditions. In the model, "users" and "conditions" are treated as random-effects variables. The independent variables related to PMT are derived from the survey questions presented in Appendix C:

- "Flood severity" was calculated by averaging Q1_1 through Q1_4: During a flood, I could lose valuable possessions; during a flood, I could lose my life or my health could suffer; during a flood, I could get injured; during a flood, my family or friends could lose their lives or their health.
- "Flood risk" was calculated by averaging Q2_1 through Q2_4: The flood risk problem concerns me, my family and friends; I could be in danger due to a flood; There is a risk of flooding in my place of residence; A flood could occur in the area where my home is located.
- "Flood fear" was calculated by averaging Q3_1 through Q3_5: I am terrified to think about the consequences of a flood; I dread to think about the consequences of a flood; Thinking about the consequences of a flood makes me feel tense; Thinking about the consequences of a flood makes me feel anxious; I get nervous when I think about the consequences of a flood.

Furthermore, participants' self-evaluations of "response efficacy", "self-efficacy" and "response costs" for both views of walking and driving are used separately in the models:

- "Response efficacy" used the average value of Q4_1 to Q4_4 for walk view and the average value of Q5_1 to Q5_4 for drive view: During a flood risk, I should take actions that are recommended in the messages to avoid the negative consequences of a flood; during a flood, following the recommendations included in the messages preserves health and saves lives; following the flood prevention recommendations included in the messages prevents your possessions from being lost or damaged; believe that what the messages request us to do during a flood risk effectively protects us from negative consequences of floods.
- "Self-efficacy" used the average value of Q4_4 to Q4_8 for walk view and the average value of Q5_3

to Q5_8 for drive view: It would be easy for me to apply all the recommendations;I am convinced that I would have no problems following all the recommendations; I would be able to prepare all the necessary items, even if it was burdensome; No matter what actions were necessary to protect myself from a flood, I would have no problem taking them. If any of the recommended actions that increased my chances of surviving a flood were a problem to me, I would find a way to deal with it.

- "Response costs" used the average value of Q4_9 to Q4_11 for walk view and the average value of Q5_9 to Q5_11 for drive view: complying with the flood prevention recommendations of emergency services would take me too long; following all of the recommendations of emergency services during a flood risk is nothing but unnecessary panic; I would follow flood recommendations reluctantly, because I would feel stupid fulfilling the 'wishes' of emergency services.

Lastly, we incorporated participants' demographic data, body heights, and levels of 3D sickness into the models, conducting separate analyses for the "first time", "second time" and "third time" responses, as well as "threat confirmation", "motivation loss", and "risk tolerance". The model information is presented as follows:

$$\begin{aligned} Y_{ij} = &\beta_0 + \beta_1 \text{Flood severity}_{ij} + \beta_2 \text{Flood risk}_{ij} + \beta_3 \text{Flood fear}_{ij} + \\ &\beta_4 \text{Response efficacy}_{ij} + \beta_5 \text{Self-efficacy}_{ij} + \beta_6 \text{Response costs}_{ij} \\ &+ \beta_7 \text{Age}_{ij} + \beta_8 \text{Gender}_{ij} + \beta_9 \text{Education}_{ij} + \beta_{10} \text{Income}_{ij} \\ &+ \beta_{11} \text{Flood experience}_{ij} + \beta_{12} \text{training}_{ij} + \beta_{13} \text{Flood knowledge}_{ij} + \\ &\beta_{14} \text{Body Height}_{ij} + \beta_{15} \text{3D Sickness}_{ij} + u_i + v_j + \epsilon_{ij} \end{aligned} \tag{1}$$

Where:

- y_{ij}: The response time for the i-th user under the j-th condition.
- β_0: The fixed intercept.
- $\beta_1, \beta_2, \ldots \beta_{15}$: The coefficients for the fixed effects.
- u_i: The random intercept for the i-th user, assumed to follow $u_i \sim \mathcal{N}(0, \sigma_u^2)$.
- v_j: The random intercept for the j-th condition is assumed to follow $v_j \sim \mathcal{N}(0, \sigma_v^2)$.
- ϵ_{ij}: The residual term is assumed to follow $\epsilon_{ij} \sim \mathcal{N}(0, \sigma_\epsilon^2)$.

4 Results

Of our 50 participants, we found that women generally respond later in the three stages than their counters, regardless of whether they are walking or driving, as shown in Figure 4. For example, it takes an average of 32.3 seconds for females to recognize a life-threatening situation and leave, compared to 30.1 seconds for males in walk view. Similarly, it takes an average of 29.5 seconds for women to leave in the drive view, while 27.6 seconds for men. The difference between the genders is not that great, but we can see that in general, males report danger earlier. Several other studies have also examined gender differences in flood risk perception (Cvetković et al., 2017; McDowell et al., 2020) and found that men showed greater confidence and preparedness (Cvetković et al., 2018; Cvetković et al., 2017), while women, despite their greater awareness and sensitivity to flood risks (De Silva and Jayathilaka, 2014), exhibited lower levels of preparedness and response actions (Cvetković et al., 2018).

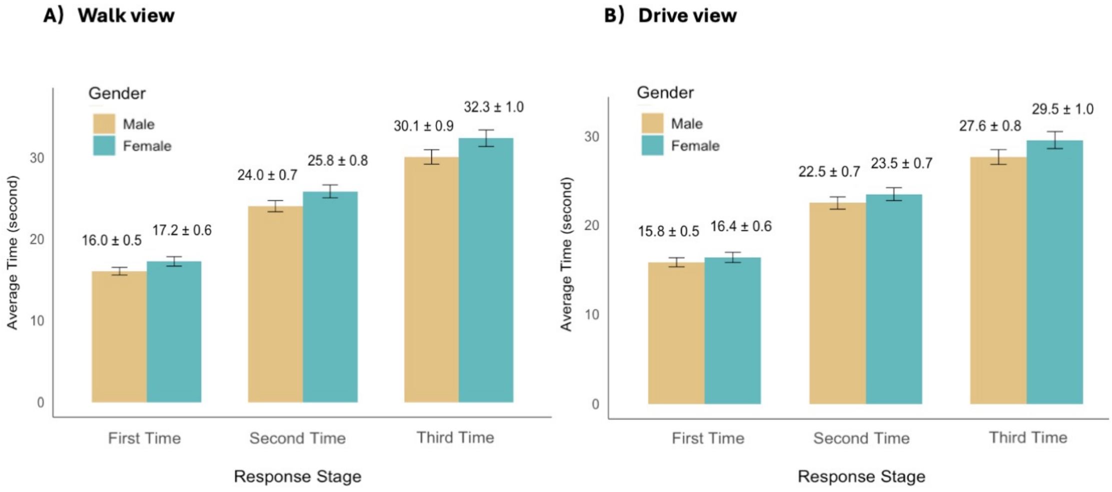

Figure 4: Response different between gender in different views: A)shows the response difference between male and female in walk view; B)shows the response difference between male and female in drive view. The bar plots display average scores with standard error bars. All response times are measured in seconds.

Furthermore, we found that people who had experienced flooding before - regardless of how often - reported danger and risks earlier than those who had never experienced flooding (n = 17), as shown in Table 2. This suggests that people without previous flood experience took longer to recognize potential risks and might miss the optimal time to evacuate. Previous studies also underscored the importance of individual past experience of floods in understanding protective behavior in the context of increasing flood frequencies (Köhler and Han, 2024; Savari et al., 2025). We also found that people who self-recognized that their knowledge of floods is ”poor" (n = 10) tend to respond more sensitively even in the initial stage of rain; this could imply that these people are more anxious than people who have a fair or good knowledge of floods when flooding occurred. This aligns with the findings of Miceli et al. (2008), which indicate that people who have previously received information or training related to flooding reported higher levels of preparedness compared to those who have not.

Feature	View	Condition Category	Number	First Time	Second Time	Third Time
Flood experience	Walk	Frequently (Annually)	n = 1	9.81	13.96	18.54
		Occasionally (Every few years)	n = 6	17.90	25.84	32.22
		Rarely (Once or twice)	n = 26	16.42	23.56	29.56
		Never	n = 17	16.68	26.99	33.70
	Drive	Frequently (Annually)	n = 1	9.68	13.35	15.30
		Occasionally (Every few years)	n = 6	14.46	21.82	27.61
		Rarely (Once or twice)	n = 26	16.04	22.09	27.64
		Never	n = 17	17.04	25.08	30.75
Flood knowledge	Walk	Poor	n = 10	13.87	21.43	28.24
		Fair	n = 24	17.96	26.18	32.43
		Good and very good	n = 16	16.11	24.87	30.79
	Drive	Poor	n = 10	14.59	21.26	27.62
		Fair	n = 24	16.39	22.96	28.54
		Good and very good	n = 16	16.48	23.83	28.83

Table 2: Comparison of human responses based on flood experience and knowledge in walk view and drive view. All response times are measured in seconds. All response times are measured in seconds.

Table 3 shows the variations of the human response under different conditions. In general, people tend to report earlier when they are in the car (first time = 16.06 seconds, second time = 22.90 seconds, third time = 28.45 seconds) than when walking down the street (first time = 16.5 seconds, second time = 24.8 seconds, third time = 31.07 seconds). This indicated that people might be more sensitive to urban contexts when they are in cars. The difference between the views of “walk" and “drive" becomes more obvious as the flooding situation is exacerbated. One possible explanation is that individuals may find it more difficult to accurately assess the depth of water in a vehicle, which may influence drivers to report risks earlier. Pearson and Hamilton (2014) compared people’s willingness to of driving through the flooded waterway in the 20-cm scenario and the 60-cm scenario and found that perceived severity significantly contributed to the decrease in the willingness to drive through the flooded waterway in the 60-cm scenario. We also found that people respond very quickly when heavy rain occurs compared to normal rain and respond slightly faster at night compared to during the day in Table 4. It also shows that people can make faster decisions when they hear a warning notification.

View	Condition Category	First Time	Second Time	Third Time
Walk	Day, Heavy rain, Alarm	12.18	17.97	21.53
	Day, Heavy rain, No alarm	12.19	17.76	21.98
	Day, Normal rain, Alarm	21.02	31.57	40.08
	Day, Normal rain, No alarm	21.58	32.28	40.91
	Night, Heavy rain, Alarm	12.56	17.82	21.76
	Night, Heavy rain, No alarm	12.15	18.10	21.81
	Night, Normal rain, Alarm	20.38	31.02	39.36
	Night, Normal rain, No alarm	20.36	31.93	41.13
	Average in all conditions	16.55	24.81	31.07
Drive	Day, Heavy rain, Alarm	10.75	15.21	18.66
	Day, Heavy rain, No alarm	11.04	15.74	19.15
	Day, Normal rain, Alarm	21.59	30.35	37.78
	Day, Normal rain, No alarm	22.40	31.31	38.57
	Night, Heavy rain, Alarm	10.46	14.91	18.75
	Night, Heavy rain, No alarm	10.48	15.26	19.04
	Night, Normal rain, Alarm	20.03	30.00	37.79
	Night, Normal rain, No alarm	21.73	30.40	37.86
	Average in all conditions	16.06	22.90	28.45

Table 3: Overview of human responses across eight experimental conditions in two views. All response times are measured in seconds.

			First Time	Second Time	Third Time	Threat Confirmation	Motivation Loss	Risk Tolerance
Walk	Illumination	Day	16.74	24.90	31.12	14.26	14.77	23.28
		Night	16.36	24.72	31.01	14.42	14.70	23.34
	Rain level	Heavy	12.27	17.91	21.77	10.42	9.66	15.97
		Normal	20.83	31.70	40.37	18.26	19.81	30.65
	Warning	Alarm	16.54	24.60	30.68	14.04	14.53	22.96
		No alarm	16.57	25.02	31.46	14.64	14.93	23.65
Drive	Illumination	Day	16.44	23.15	28.54	11.73	12.51	19.89
		Night	15.68	22.64	28.36	11.96	13.01	20.37
	Rain level	Heavy	10.68	15.28	18.90	7.88	8.28	13.29
		Normal	21.44	30.52	38.00	15.80	17.24	26.97
	Warning	Alarm	15.71	22.62	28.24	11.72	12.76	20.09
		No alarm	16.41	23.18	28.65	11.97	12.75	20.17

Table 4: Comparison of human responses across different experimental conditions: lighting (day and night), rain level (normal and heavy), and warning types (no notification and alarm notification). All response times are measured in seconds.

Figure 5 shows the distribution of the human response under the different conditions. The variation in the three responses of the participants to rain levels is consistent. However, for both warning types and lighting conditions, while most participants' initial responses occur within 20 seconds, subsequent second and third responses display greater variability. This trend indicates both prolonged and immediate response. Prolonged responses may suggest that some individuals exhibit a higher level of self-confidence and consequently underestimate flood risks, while immediate responses may indicate anxiety about potential flooding, thus prompting rapid evacuation. For example, the maximum third response time, 61.32 seconds in the driving view and 73.96 seconds in the walking view under alarm conditions—contrast with those under no alarm conditions ($\max_{drive}$ = 61.53 seconds and $\max_{walk}$ = 75.53 seconds), suggesting that some participants may not have considered the alarm. Previous studies have also emphasized the importance of flood early warning systems in reducing human casualties (Ringo et al., 2024), but also noted that a longer lead time for early flood warnings does not guarantee better evacuation performance (Zhang et al., 2024).

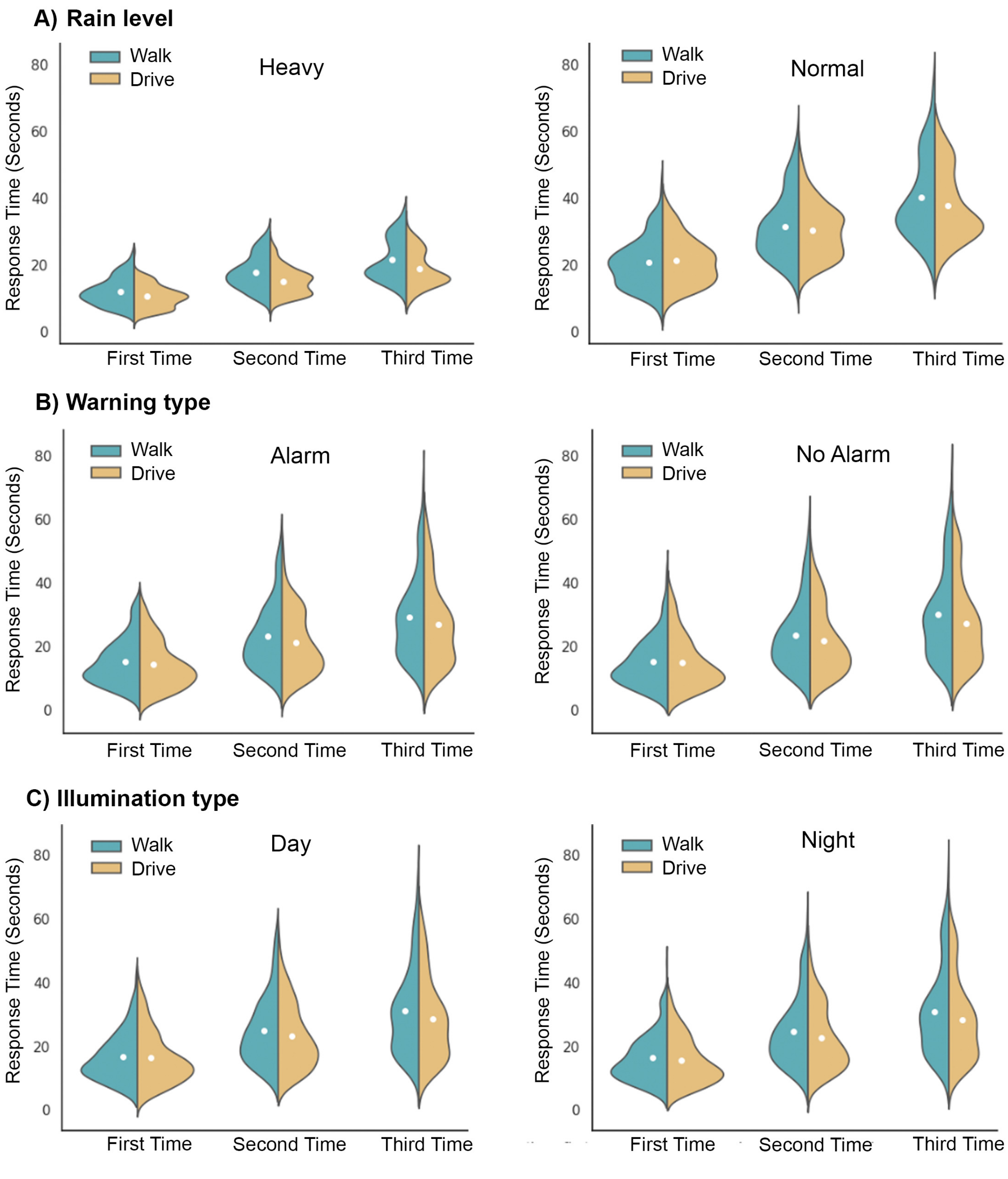

Figure 5: The distribution of human responses for walk view and drive view in three conditions: A) rain level, B) warning type, and C) illumination type. The violin plots show the data distribution with the mean values. All response times are measured in seconds.

4.1 ANOVA Test

The repeated measures ANOVA was utilized to analyze temporal response variations among the same subjects across different conditions of “rain level", “warning", and “illumination". This analysis further highlighted the distinctions between the walk view and the drive view. For both views, repeated measures ANOVA indicated a significant main effect of “rain level" as shown in Figure 6. For example, $F(1,49) = 1407.54, p < 0.001$ for the third time in the walk view and $F(1,49) = 7184.94, p < 0.001$ for the third time in the drive view. Regarding the drive view, our findings indicate that alarm notifications significantly affect human response times, occurring three times. Specifically, $F(1,49) = 7.42, p < 0.01$ for the third time and $F(1,49) = 5.02, p < 0.05$ for the second response time in the drive view.

Furthermore, the first and second response times of the individuals also varied significantly between the day and night conditions in the drive view ($p <$ 0.05). Additionally, no significant differences were found for ’warning’ and ’illumination’ in the walk view. These findings suggest that human decision making timing in vehicles is particularly sensitive to contextual information, such as warning settings and illumination conditions. Previous studies have also emphasized the impact of low visibility during bad weather, which can increase drivers’ perception of risk and anxiety while driving (Wang et al., 2002; Sheeny et al., 2021). The complete results of the ANOVA test are presented in Appendix E, and complete box plots of user response times under different conditions of “rain level", “warning", and “illumination" for both walk and drive views can be found in Appendix D.

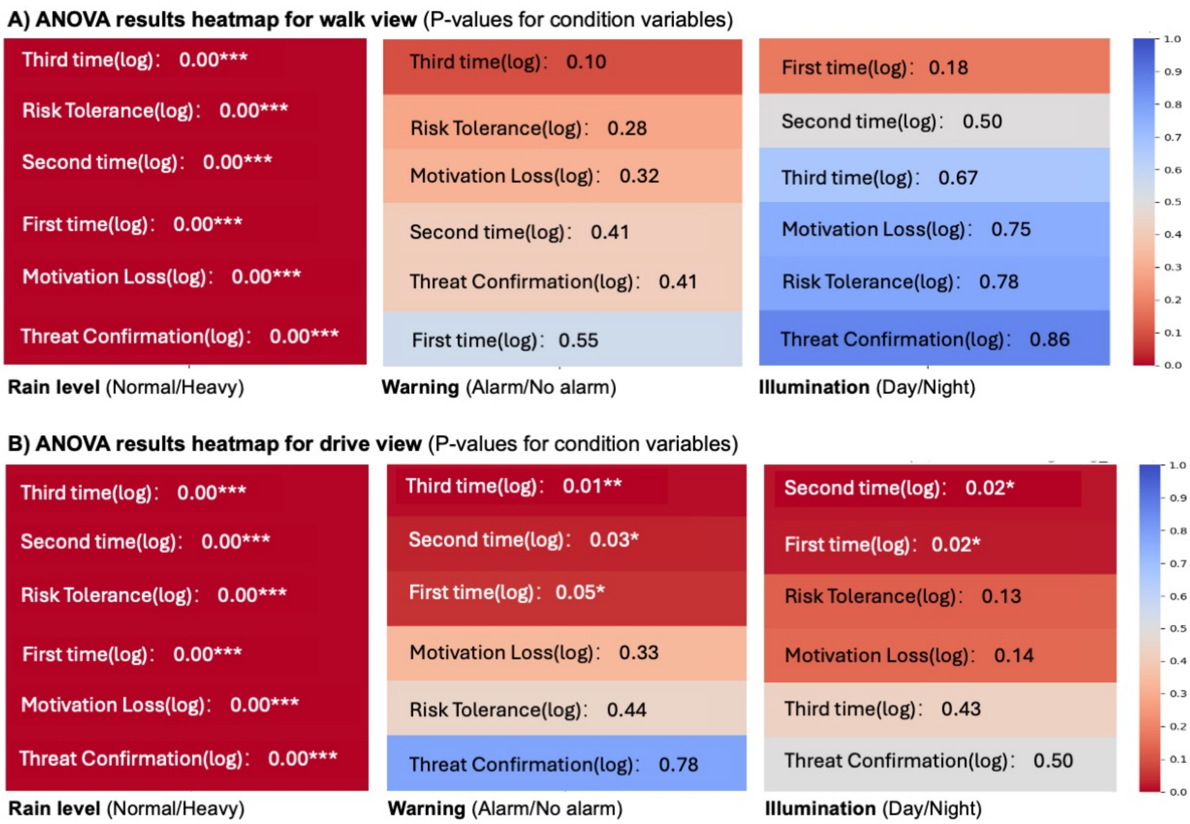

Figure 6: Result of the repeated measures ANOVA test, taking into account the rain level, alarm setting, and lighting setting in both the walk and drive views. Significance levels are shown as follows: $p < 0.001$ ***; $p < 0.01$ **, $p < 0.05$ *.

4.2 Linear Mixed-Effects Models

Linear mixed-effects models were employed with human response time as the dependent variable. In addition to including the first time (log), the second time (log), and the third time (log) as predictors, this paper also examined the temporal intervals between responses. Thus, threat confirmation (log), motivation loss (log), and risk toleration (log) were used to evaluate the transition stages of individuals during flooding events. The analysis aimed to investigate the associations between general perceptions of flood risk by individuals, beliefs in self-efficacy, demographic factors, flood experience, and human decision-making processes during flood events.

The results indicate a significant negative association between self-efficacy and the first time response (β = -0.22, $p \leq 0.05$) and the second time response (β = -0.17, $p < 0.05$) and the third time response (β = -0.16, $p < 0.05$) for the walk view, as illustrated in Table 5. Furthermore, the analysis demonstrates a negative association with the first time response (β = -0.25, $p < 0.01$) and the second time response (β = -0.18, $p \leq 0.05$) for the drive view, as illustrated in Table 6. These findings suggest that individuals with higher self-efficacy can identify abnormal weather events (e.g.,rain) and recognize when conditions become "dangerous" or "life-threatening" earlier in the experiment. Similar findings were also found in previous studies that people with high efficacy beliefs were more likely to take self-protective behaviors (Kievik and Gutteling, 2011; Grothmann and Reusswig, 2006). However, no significant association was identified between response times by individuals and their general perception of the severity, risk, and fear of the flood during this flood experiment in this study. The complete model results can be found in Appendix F.

Furthermore, this study demonstrates that both education and income negatively influence human responses, indicating that higher levels of education and income may lead to earlier detection of danger in flood scenarios. Specifically, the income level is negatively associated with the third response time (β = -0.05, $p < 0.05$), the threat confirmation time (β = -0.09, $p < 0.05$), the motivation loss time (β = -0.14, $p < 0.01$) and the risk tolerance time (β = -0.09, $p < 0.01$) from a walk view in Table 5. This indicates that people with higher income levels might be more likely to evacuate earlier after recognizing danger in the final phase. Likewise, the income level is negatively associated with the first time response (β = -0.05, $p < 0.05$), the second time response (β = -0.05, $p \leq 0.05$), the third time response (β = -0.06, $p < 0.05$), the threat confirmation time (β = -0.09, $p < 0.05$), the motivation loss time (β = -0.15, $p < 0.01$) and the risk tolerance time (β = -0.09, $p < 0.05$) in a driving context. Furthermore, no significant correlation was observed between response times and other individual factors, such as flood experience, training, and knowledge.

Lastly, this paper finds that a higher education level is negatively associated with the threat confirmation time (β = -0.24, $p < 0.05$) and the risk toleration time (β = -0.22, $p < 0.05$) in a drive view. This indicates that people with higher education tend to take less time to confirm the threat and choose to leave earlier when they are in the car. No significant association was found between education and human responses in a walking context. In addition, the age level shows a negative association with the first response time (β = -0.12, $p < 0.05$) in the drive view. Although previous studies have emphasized the positive influence of education and income levels on flood preparedness (Gülsoy et al., 2025; Jahan Nipa et al., 2020), this study offers new empirical evidence from human-computer interaction within a virtual flood simulation.

Variables	First time(log)	Second time(log)	Third time(log)	Threat Confirmation(log)	Motivation Loss(log)	Risk Tolerance(log)
Fixed effect	**Estimate (Std.)**	**Estimate (Std.)**	**Estimate (Std.)**	**Estimate (Std.)**	**Estimate (Std.)**	**Estimate (Std.)**
(Intercept)	4.08 (1.18)**	4.3 (1.05)***	4.95 (1.06)***	3.25 (2.06)	6.06 (2.16)**	4.6 (1.62)**
Flood severity	0.07 (0.09)	0.06 (0.08)	0.06 (0.08)	0.1 (0.16)	0.07 (0.16)	0.06 (0.12)
Flood risk	0.03 (0.08)	0.04 (0.07)	0.04 (0.07)	0.04 (0.14)	0.02 (0.15)	0.04 (0.11)
Flood fear	0 (0.06)	0 (0.06)	-0.01 (0.06)	-0.06 (0.11)	-0.04 (0.12)	-0.05 (0.09)
Response efficacy	-0.03 (0.09)	-0.05 (0.08)	-0.08 (0.08)	-0.08 (0.16)	-0.25 (0.17)	-0.11 (0.13)
Self-efficacy	-0.22 (0.09)*	-0.17 (0.08)*	-0.16 (0.08)*	-0.16 (0.15)	-0.17 (0.16)	-0.14 (0.12)
Response costs	0.04 (0.07)	0.01 (0.06)	0.02 (0.06)	0.02 (0.12)	0.06 (0.13)	0 (0.1)
Gender	0.03 (0.11)	0.05 (0.1)	0.05 (0.1)	0.19 (0.19)	0.07 (0.2)	0.12 (0.15)
Age	-0.09 (0.06)	-0.02 (0.05)	-0.01 (0.05)	0.09 (0.11)	0.07 (0.11)	0.07 (0.08)
Education	0.09 (0.06)	-0.04 (0.05)	-0.07 (0.06)	-0.17 (0.11)	-0.18 (0.11)	-0.15 (0.08)
Income	-0.04 (0.02)	-0.04 (0.02)	-0.05 (0.02)*	-0.09 (0.04)*	-0.14 (0.04)**	-0.09 (0.03)**
Experience	-0.01 (0.06)	0.04 (0.05)	0.03 (0.05)	0.16 (0.11)	-0.04 (0.11)	0.08 (0.08)
Trainings	-0.12 (0.12)	-0.11 (0.1)	-0.12 (0.1)	-0.08 (0.2)	-0.19 (0.21)	-0.1 (0.16)
Knowledge	0.06 (0.07)	0.07 (0.06)	0.06 (0.06)	0.09 (0.12)	0.02 (0.13)	0.05 (0.1)
Height	0 (0.01)	0 (0.01)	0 (0.01)	0 (0.01)	0 (0.01)	0 (0.01)
Sickness	0.02 (0.02)	0.02 (0.02)	0.02 (0.02)	0.01 (0.04)	0.03 (0.04)	0.01 (0.03)
Random effect	**Variance (Std.Dev.)**	**Variance (Std.Dev.)**	**Variance (Std.Dev.)**	**Variance (Std.Dev.)**	**Variance (Std.Dev.)**	**Variance (Std.Dev.)**
User ID	0.07 (0.27)	0.06 (0.24)	0.06 (0.25)	0.23 (0.48)	0.25 (0.5)	0.14 (0.38)
Condition	0.07 (0.26)	0.08 (0.29)	0.1 (0.32)	0.07 (0.26)	0.11 (0.33)	0.1 (0.32)
Residual	0.03 (0.17)	0.02 (0.13)	0.01 (0.11)	0.08 (0.29)	0.11 (0.33)	0.04 (0.2)
Conditional R2	0.85	0.90	0.93	0.82	0.81	0.88
Marginal R2	0.13	0.11	0.12	0.16	0.17	0.15

Table 5: Summary of Mix-linear Regression for walk view. Significance levels are shown as follows: $p < 0.001$ ***; $p < 0.01$ **, $p < 0.05$ *.

Variables	First time(log)	Second time(log)	Third time(log)	Threat Confirmation(log)	Motivation Loss(log)	Risk Tolerance(log)
Fixed effect	**Estimate (Std.)**	**Estimate (Std.)**	**Estimate (Std.)**	**Estimate (Std.)**	**Estimate (Std.)**	**Estimate (Std.)**
(Intercept)	3.74 (1.15)**	3.76 (1.06)**	4.39 (1.11)***	2.91 (2.3)	6.01 (2.78)*	3.94 (1.96)
Flood severity	0 (0.08)	0 (0.07)	-0.02 (0.08)	0.03 (0.16)	-0.05 (0.2)	0 (0.14)
Flood risk	-0.04 (0.08)	-0.03 (0.07)	-0.03 (0.07)	-0.1 (0.15)	-0.11 (0.18)	-0.08 (0.13)
Flood fear	0.05 (0.06)	0.05 (0.06)	0.04 (0.06)	0.03 (0.12)	0.06 (0.15)	0.01 (0.1)
Response efficacy	0.02 (0.08)	0.02 (0.08)	0.01 (0.08)	0 (0.16)	-0.1 (0.2)	-0.01 (0.14)
Self-efficacy	-0.25 (0.09) **	-0.18 (0.08)*	-0.14 (0.09)	-0.17 (0.18)	-0.11 (0.22)	-0.1 (0.16)
Response costs	-0.02 (0.08)	-0.03 (0.07)	-0.02 (0.07)	-0.07 (0.15)	0.07 (0.18)	-0.02 (0.13)
Gender	0.07 (0.1)	0.11 (0.09)	0.1 (0.1)	0.32 (0.2)	0.09 (0.25)	0.21 (0.17)
Age	-0.12 (0.06)*	-0.05 (0.06)	-0.03 (0.06)	0.06 (0.12)	0.03 (0.15)	0.06 (0.1)
Education	0.08 (0.06)	-0.05 (0.05)	-0.08 (0.05)	-0.24 (0.11)*	-0.28 (0.14)	-0.22 (0.1)*
Income	-0.05 (0.02)*	-0.05 (0.02)*	-0.06 (0.02)*	-0.09 (0.04)*	-0.15 (0.05)**	-0.09 (0.04)*
Experience	0 (0.06)	0.03 (0.05)	0.03 (0.06)	0.09 (0.12)	0 (0.15)	0.09 (0.1)
Trainings	-0.1 (0.13)	-0.12 (0.12)	-0.09 (0.12)	-0.15 (0.26)	-0.17 (0.31)	-0.07 (0.22)
Knowledge	0.09 (0.07)	0.07 (0.06)	0.05 (0.06)	0.08 (0.13)	-0.02 (0.16)	0.02 (0.11)
Height	0 (0.01)	0 (0)	0 (0.01)	0 (0.01)	0 (0.01)	0 (0.01)
Sickness	0.01 (0.02)	0.01 (0.02)	0 (0.02)	0.01 (0.05)	-0.03 (0.06)	-0.01 (0.04)
Drive ability	0.11 (0.07)	0.11 (0.07)	0.11 (0.07)	0.12 (0.14)	0.13 (0.17)	0.09 (0.12)
Random effect	**Variance (Std.Dev.)**	**Variance (Std.Dev.)**	**Variance (Std.Dev.)**	**Variance (Std.Dev.)**	**Variance (Std.Dev.)**	**Variance (Std.Dev.)**
User ID	0.06 (0.25)	0.06 (0.24)	0.06 (0.25)	0.26 (0.51)	0.39 (0.62)	0.19 (0.44)
Condition	0.12 (0.35)	0.12 (0.35)	0.13 (0.36)	0.11 (0.33)	0.12 (0.35)	0.13 (0.36)
Residual	0.03 (0.16)	0.01 (0.09)	0.01 (0.07)	0.06 (0.25)	0.06 (0.25)	0.03 (0.17)
Conditional R2	0.89	0.96	0.98	0.88	0.91	0.93
Marginal R2	0.12	0.1	0.1	0.15	0.19	0.16

Table 6: Summary of Mix-linear Regression for drive view. Significance levels are shown as follows: $p < 0.001$ ***; $p < 0.01$ **, $p < 0.05$ *.

5 Discussion

This paper presents a novel approach to examining decision making during floods, utilizing individual-level experiences within VR-supported simulations of flood scenarios. Using virtual reality and three-dimensional simulations, the study initially evaluated individual responses under three conditions (i.e., illumination, rain level, and warning type) and two views (i.e., walk view and drive view). The results show that people reported significantly different between normal rain and flash floods, and people are more likely to report hazards earlier at night than during the day and to evacuate quickly when alerted by an alarm. This suggests that people are more sensitive to alarms and night-time when people are in the car. The results are consistent with previous research that has highlighted that drivers' perceptions of safety are positively influenced by clear visibility (Wang et al., 2002; Sheeny et al., 2021), while poor weather and low light conditions increase people's anxiety, particularly in the case of rain and flooding (Kilpeläinen and Summala, 2007; Cianconi et al., 2020). Based on our findings, we suggest that increasing the awareness of contextual information in people while in a vehicle will improve their estimation of potential hazards and contribute to vehicle safety on the road during floods (Xia et al., 2011; Pregnolato et al., 2017). Future research could explore the integration of additional vehicle guidance and warning systems to facilitate timely evacuation from life-threatening situations.

However, during this study, we observed that some participants did not comply with the warnings, which is consistent with previous studies indicating that warnings do not guarantee better evacuation performance. For example, the uncertainty of people's decision to evacuate impacts their actual evacuation behavior. In some situations, people tend to wait for others to evacuate, especially when no pioneer is evacuating (Zhang et al., 2024). However, this study did not take into account the behavior of other pedestrians and drivers on the road. For example, Coles and Hirschboeck (2020) noted that the factors that influence driver decisions include previous successful crossings of other vehicles and the presence of passengers. Previous studies have identified phenomena known as the "cry wolf effect" (Sawada et al., 2022; Lim et al., 2019) and "alarm fatigue" (Laumonier et al., 2017), referring to the exhaustion experienced by individuals as a result of too many false alarms. In our studies, participants had to complete a total of 32 trials in 40 minutes. This duration may contribute to increased fatigue and may also influence other variables. Future research should incorporate additional agents into virtual reality simulations or integrate agent-based modeling to explore how individual decision-making processes are influenced by the behaviors of other passengers and drivers in relation to social and flooding dynamics.

In addition, this paper examines how people's prior perceptions of flooding and their beliefs in self-protection capabilities during flood preparedness influence their decision making in flood situations. Although previous studies have shown that previous flood experience (Grothmann and Reusswig, 2006) or direct flood simulation experience (Zaalberg and Midden, 2010), training(Peden et al., 2023), flood knowledge (Hirunsalee and Kanegae, 2012) can significantly increase the probability of flood protective behavior (Grothmann and Reusswig, 2006), the mixed linear regression in this paper did not show significance. Our results show that people's confidence in self-protection significantly impacts their earlier response to flooding, which is consistent with the findings of many previous research on the positive impact of efficacy beliefs during flood response (Kievik and Gutteling, 2011; Grothmann and Reusswig, 2006), suggesting that improving self-efficacy could allow people to remain alert and take timely actions in response to flooding. Many research studies also mentioned that this confidence can be strengthened through training in effective self-protection strategies (Peden et al., 2023; Hirunsalee and Kanegae, 2012). Future studies can conduct the comparison between "before training" and "after training" using virtual reality to examine preparedness for flooding.

However, the results of this study did not reveal a significant association between human response time and general understanding of severity, risks, or fear of flooding, while previous work found that feelings of worry were associated with disaster preparedness (Miceli et al., 2008). This finding may be related to the behavior-intent gap discussed in previous studies (Osberghaus et al., 2025). In our study, more than 80% of the participants acknowledged that floods pose significant risks from the pre-experiment survey; however, this recognition may not translate into action during actual flooding events, as noted in the studies of Osberghaus et al. (2025) and Bamberg et al. (2017). Consequently, while this study assessed participants' general perceptions regarding flooding, these perceptions may not correlate with the VR-based simulated flood scenarios. Furthermore, many participants had no prior flooding experience; therefore, their perceptions of severity, risk, and fear were based on hypothetical scenarios rather than actual experiences. In addition to assessing individuals' baseline understanding of flooding situations prior to virtual reality (VR) experiences, future research should investigate participants' general perceptions within the VR-based flooding scenarios, which reflect the flooding they encounter in the measurement.

The results of this paper also show the gender difference that women take longer to make decisions in the face of flood risk. Our findings suggest that women may have a higher tolerance for risk than men, or may react later due to perceived greater uncertainty in risk assessment. Previous studies have shown that women are more vulnerable to flood disasters compared to men (De Silva and Jayathilaka, 2014), but women also show a deeper understanding of flood risk, while men seem to be more confident in their ability to cope with floods and make decisions based on their social roles (Cvetković et al., 2017). In light of this, more research is needed to understand the reasons for women's longer response times and to explore the truth of gender differences in human real-time response during floods. Additionally, the results of the mixed-effects regression analysis drew our attention to levels of education and income. Previous studies also found that levels of education and income were associated with levels of disaster literacy and preparedness for disasters (Gülsoy et al., 2025; Jahan Nipa et al., 2020). For example, Grothmann and Reusswig (2006) found that the variables in the socioeconomic model that produce statistically significant correlations with protective responses were age, household income, and home ownership. In particular, household income was a statistically significant predictor for the purchase of flood protection devices. Future studies can conduct more controlled experiments to examine how socioeconomic characteristics are associated with action-based disaster evacuation.

There are several limitations to consider. First, this article involved 50 participants, which is not a small number compared to other VR-based studies; however, all participants were recruited through university channels, which may also limit the impact of demographic variables on the results. Future studies should explore the potential of VR-based measures in broader populations and compare differences in responses between different demographic groups. In addition, the 3D sickness of using VR devices in urban scenarios (Polcar and Horejsi, 2013) should also be considered in the study design phrase, which may require researchers to simplify the interaction to increase applicability and inclusivity for people of different backgrounds. Looking to the future, we anticipate that advances in virtual reality technology will alleviate concerns about 3D sickness. This immersive experience is expected to increase participants' awareness of flood emergencies and equip them with critical skills for timely decision making.

Second, this paper created a small-scale street environment in Unity, where participants were instructed to walk forward and backward within the confined area of the virtual world. As a result, after several trials, the participants may have discerned the pattern of increase in water. In addition, the increase in water in the study was linear, allowing participants to learn to calculate the height of the flood over time. Future research could utilize diverse environments to enhance participants' experiences and incorporate variations in topological height to improve dynamic changes in water levels (Zhang et al., 2020). Furthermore, future studies could examine the buoyancy of water and scenarios in which the car floats as water levels rise from the perspective of an occupant inside the vehicle.

Lastly, we implemented a continuous alarm notification in this paper; Once the alarm is activated based on the height of the water, it persists until the trial is over. As a result, participants who are still in the flood environment may choose to leave due to the annoyance caused by the alarm. Future studies could benefit from incorporating varying warning systems (Marzukhi et al., 2018; Mileti, 1995), such as an initial reminder via an alarm message, followed by a short-term alarm sound and subsequently a long-term alarm sound to study how the alarm system can adjust people's self-protection motivation and danger perception.

6 Conclusion

This paper evaluates human decision making on evacuation in flood risk scenarios through VR-based human-environment interaction and examines the variability in responses based on contextual information. Furthermore, this study analyzes the association between individuals' perceptions of flooding, the efficacy beliefs, and their responses during flood events. The findings indicate that people are more aware of the risks of floods when driving and at night compared to during the day. In addition, education and income levels may be significantly associated with faster responses, and people who have confidence in their ability to protect themselves are more likely to take decisive and timely action. We anticipate that the findings of this paper will assist policy makers in developing practical strategies for self-protection, increasing public awareness of flooding, and equipping individuals with skills to recognize danger earlier and learn self-protection strategies.

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9 Author contributions statement

Zhaoxi Zhang: Methodology, Data collection, Formal analysis, Original draft writing, Review writing. **Qinchan Li**: Conceptualization, Methodology, Software. **Qi Sun**: Conceptualization, Device, Review, Supervision. **Luis Ceferino** : Conceptualization, Review, Supervision. All authors reviewed the manuscript.

10 Declarations

Ethics or approval statement: This study was reviewed and approved by the Institutional Review Board (IRB) at New York University (IRB Protocol: IRB-FY2023-7548; Title: Virtual and Augmented Reality for Community Preparedness to Disasters). **Competing interests**: The authors declare no conflict of interest. **Funding**: This study receive no funding.

11 Data availability statement

The datasets generated during and/or analyzed during the current study are not publicly available due to the IRB requirements and confidentiality agreements.

12 Appendix A

Pre-experiment Survey

Thank you for taking the time to participate in our study "Virtual and Augmented Reality for Community Preparedness to Disasters". Your insights are invaluable to us and will contribute significantly to our understanding of human self-protection motivation and behavior in the face of flooding and help us improve flood preparedness in community. Please complete the survey under the guidance of the investigator.

Please enter the participation ID provided by the investigator. Do not include any personal information.

____

Q1: In general, please indicate how you agree or disagree with the following statement about the severity of flooding.

	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1-During a flood, I could lose valuable possessions.					
2-During a flood, I could lose my life or my health could suffer.					
3-During a flood, I could get injured.					
4-During a flood, my family or friends could lose their lives or their health.					

Q2: In general, please indicate how you agree or disagree with the following statements about flood risks.

	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1-The flood risk problem concerns me, and my family and friends.					
2-I could be in danger due to a flood.					
3-There is a risk of flooding in my place of residence.					
4-A flood could occur in the area where my home is located.					

Q3: Please indicate how you agree or disagree with the following statement about human fear of floods.

	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1-I am terrified to think about the consequences of a flood.					
2-I dread to think about the consequences of a flood.					
3-Thinking about the consequences of a flood makes me feel tense.					
4-Thinking about the consequences of a flood makes me feel anxious.					
5-I get nervous when I think about the consequences of a flood.					

Q4: Please indicate how you agree or disagree with the part of the self-protection messages related to walking on the street.

	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1-During a flood risk, I should take actions that are recommended in messages to avoid the negative consequences of a flood.					
2-During a flood, following the recommendations included in the messages preserves health and saves lives.					
3-Following the flood-prevention recommendations included in the messages prevents your possessions from being lost or damaged (e.g. flooded home or car).					
4-I believe that what the messages request us to do during a flood risk effectively protects us from negative consequences of floods.					
5-It would be easy for me to apply all the recommendations.					
6-I am convinced that I would have no problems following all the recommendations.					
7-I would be able to prepare all the necessary items, even if it was burdensome.					
8-No matter what actions were necessary to protect myself from a flood, I would have no problem taking them. If any of the recommended actions that increased my chances to safely withstand a flood were a problem to me, I would find a way to deal with that.					
9-Complying with the flood prevention recommendations of emergency services would take me too long.					

10-Following all of the recommendations of emergency services during a flood risk is nothing but unnecessary panic.					
11-I would follow flood recommendations reluctantly, because I would feel stupid fulfilling the 'wishes' of emergency services.					

Q5: Please indicate how you agree or disagree with the part of the self-protection messages about staying in a car.

	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1-During a flood risk, I should take actions that are recommended in messages to avoid the negative consequences of a flood.					
2-During a flood, following the recommendations included in the messages preserves health and saves lives.					
3-Following the flood-prevention recommendations included in the messages prevents your possessions from being lost or damaged (e.g. flooded home or car).					
4-I believe that what the messages request us to do during a flood risk effectively protects us from negative consequences of floods.					
5-It would be easy for me to apply all the recommendations.					
6-I am convinced that I would have no problems following all the recommendations.					
7-I would be able to prepare all the necessary items, even if it was burdensome.					
8-No matter what actions were necessary to protect myself from a flood, I would have no problem taking them. If any of the recommended actions that increased my chances to safely withstand a flood were a problem to me, I would find a way to deal with that.					
9-Complying with the flood prevention recommendations of emergency services would take me too long.					
10-Following all of the recommendations of emergency services during a flood risk is nothing but unnecessary panic.					

11-I would follow flood recommendations reluctantly, because I would feel stupid fulfilling the ‘wishes’ of emergency services.					

Q6: How do you describe yourself?

Male

Female

Non-binary/third gender

Prefer to self-describe______

Prefer not to say.

Q7: How old are you?

Under 18

18-24 years old

25-34 years old

35-44 years old

45-54 years old

55-64 years old

65 + years old

Q8: What is the highest level of education you have completed?

Some high school or less

High school diploma or GED

Some college, but no degree

Associates or technical degree

Bachelor’s degree

Graduate or professional degree (MA, MS,MBA,PHD,JD,MD,DDS etc.)

Prefer not to say.

Q9: What was your total household income before taxes during past 12 months?

Less than $25,000

$25,000-$49,999

$50,000-$74,999

$75,000-$99,999

$100,000-$149,999

$150,000 or more

Prefer not to say.

Q10: Do you have a long-term illness, disability, or medical condition that has been diagnosed by a doctor?

Yes

No

Prefer not to say.

Q11: Are you able to drive?

No, I have never driven.

Yes, I have a driver license, but not drive often.

Yes, I often drive.

Q12: Have you ever experienced a flood?

Yes, I lived before /live now in a flood-prone area (Multiple times a year)

Frequently (Annually)

Occasionally (Every few years)

Rarely (Once or twice up to now)

Never

Q13: Have you received trainings from schools, communities, governments, etc. on how to protect yourself in the event of a flood?

Yes

No

Don't know/not sure.

Q14: Please rate how much you know about flooding.

1 = Poor

2 = Fair

3 = Good

4 = Very Good

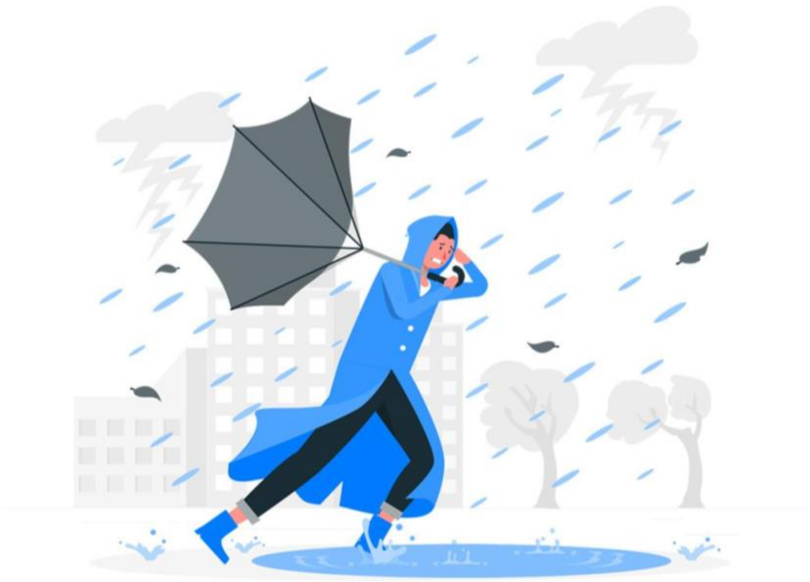
5 = Excellent

13 Appendix B

Read the Self-protection Messages carefully.

The following self-protection messages, which are related to rising water during floods, are from the official government website[1][2][3] that can help you assess your self-protection ability. You don't have to memorize the messages, but only complete the pre-experiment survey based on how you evaluate the effectiveness of the self-protection approaches mentioned here and your ability to use them in floods.

Walking on the street



- Move immediately to higher ground or stay on high ground.
- Do not walk on flood embankments.
- Do not enter the water.
- Keep calm.
- Wait for help in a safe and visible location.
- Don't walk through flood waters. It only takes 6 inches of moving water to knock you off your feet.
- Pay attention to road closure and other cautionary signs are put in place for your safety.

[1] American Safety Council website : https://blog.americansafetycouncil.com/how-to-survive-a-flash-flood-in-your-car-2/
[2] the National Weather Service: https://www.weather.gov/safety/flood-during
[3] local government agencies (the Commonwealth of Massachusetts): https://www.mass.gov/info-details/flood-safety-tips

- Water may be deeper than it appears and can hide hazards such as sharp objects, washed out road surfaces, electrical wires, chemicals, etc.
- Follow instructions from public safety officials. If advised to evacuate, do so immediately.

Staying in a car

- Repark vehicles to an elevated area.
- Do not attempt to cross flowing streams.
- Do not drive into flooded roadways or around a barricade; Turn Around, Don't Drown!
- A vehicle caught in swiftly moving water can be swept away in seconds.
- 12 inches of water can float a car or small SUV, 18 inches of water can carry away large vehicles.
- Two feet of water is enough to sweep your car off the road.
- Most automatic windows will open unless the car is submerged. This is your best bet, so open your window if you can.
- Swim out of your window.

14 Appendix C

Questions	Strongly Agree	Agree	Neutral	Disagree	Strongly Dis-agree	Total
Q1-1: During a flood, I could lose valuable possessions.	26	18	5	1	0	50
Q1-2: During a flood, I could lose my life or my health could suffer.	22	21	3	4	0	50
Q1-3: During a flood, I could get injured.	29	18	2	1	0	50
Q1-4: During a flood, my family or friends could lose their lives or their health.	20	23	6	1	0	50
Q2-1: The Flood risk problem concerns me, and my family and friends.	9	25	8	8	0	50
Q2-2: I could be in danger due to a flood.	8	32	3	7	0	50
Q2-3: There is a risk of flooding in my place of residence.	0	12	12	22	4	50
Q2-4: A flood could occur in the area where my home is located.	3	16	12	18	1	50
Q3-1: I am terrified to think about the consequences of a flood.	1	17	18	10	4	50
Q3-2: I dread to think about the consequences of a flood.	1	9	26	11	3	50
Q3-3: Thinking about the consequences of a flood makes me feel tense.	1	19	12	16	2	50
Q3-4: Thinking about the consequences of a flood makes me feel anxious.	4	15	13	15	3	50
Q3-5: I get nervous when I think about the consequences of a flood.	1	13	19	15	2	50
Q4-1(walk): During a Flood risk, I should take actions that are recommended in messages to avoid the negative consequences of a flood.	29	21	0	0	0	50
Q4-2(walk): During a flood, following the recommendations included in the messages preserves health and saves lives.	23	26	1	0	0	50
Q4-3(walk): Following the flood-prevention recommendations included in the messages prevents your possessions from being lost or damaged (e.g. flooded home or car).	12	19	8	10	1	50
Q4-4(walk): I believe that what the messages request us to do during a Flood risk effectively protects us from negative consequences of floods.	15	28	6	0	1	50
Q4-5(walk): It would be easy for me to apply all the recommendations.	9	22	16	3	0	50
Q4-6(walk): I am convinced that I would have no problems following all the recommendations.	5	23	16	6	0	50
Q4-7(walk): I would be able to prepare all the necessary items, even if it was burdensome.	3	22	18	6	1	50
Q4-8(walk): No matter what actions were necessary to protect myself from a flood, I would have no problem taking them. If any of the recommended actions that increased my chances to safely withstand a flood were a problem to me, I would find a way to deal with that.	8	27	13	2	0	50
Q4-9(walk): Complying with the flood prevention recommendations of emergency services would take me too long.	0	4	18	24	4	50
Q4-10(walk): Following all of the recommendations of emergency services during a Flood risk is nothing but unnecessary panic.	0	3	6	19	22	50
Q4-11(walk): I would follow flood recommendations reluctantly, because I would feel stupid fulfilling the 'wishes' of emergency services.	0	1	4	20	25	50
Q5-1(drive): During a Flood risk, I should take actions that are recommended in messages to avoid the negative consequences of a flood.	23	25	2	0	0	50
Q5-2(drive): During a flood, following the recommendations included in the messages preserves health and saves lives.	25	24	0	1	0	50
Q5-3(drive): Following the flood-prevention recommendations included in the messages prevents your possessions from being lost or damaged (e.g. flooded home or car).	10	20	8	11	1	50
Q5-4(drive): I believe that what the messages request us to do during a Flood risk effectively protects us from negative consequences of floods.	13	31	5	1	0	50
Q5-5(drive): It would be easy for me to apply all the recommendations.	5	22	19	4	0	50
Q5-6(drive): I am convinced that I would have no problems following all the recommendations.	3	22	21	4	0	50
Q5-7(drive): I would be able to prepare all the necessary items, even if it was burdensome.	4	23	19	4	0	50
Q5-8(drive): No matter what actions were necessary to protect myself from a flood, I would have no problem taking them. If any of the recommended actions that increased my chances to safely withstand a flood were a problem to me, I would find a way to deal with that.	13	19	15	3	0	50
Q5-9(drive): Complying with the flood prevention recommendations of emergency services would take me too long.	0	3	18	23	6	50
Q5-10(drive): Following all of the recommendations of emergency services during a Flood risk is nothing but unnecessary panic.	0	2	3	21	24	50
Q5-11(drive): I would follow flood recommendations reluctantly, because I would feel stupid fulfilling the 'wishes' of emergency services.	0	0	5	19	26	50

Table 7: Summary of the self-reported PMT survey from all participants

15 Appendix D: Box plots for three conditions: illumination, Rain level, and warning types

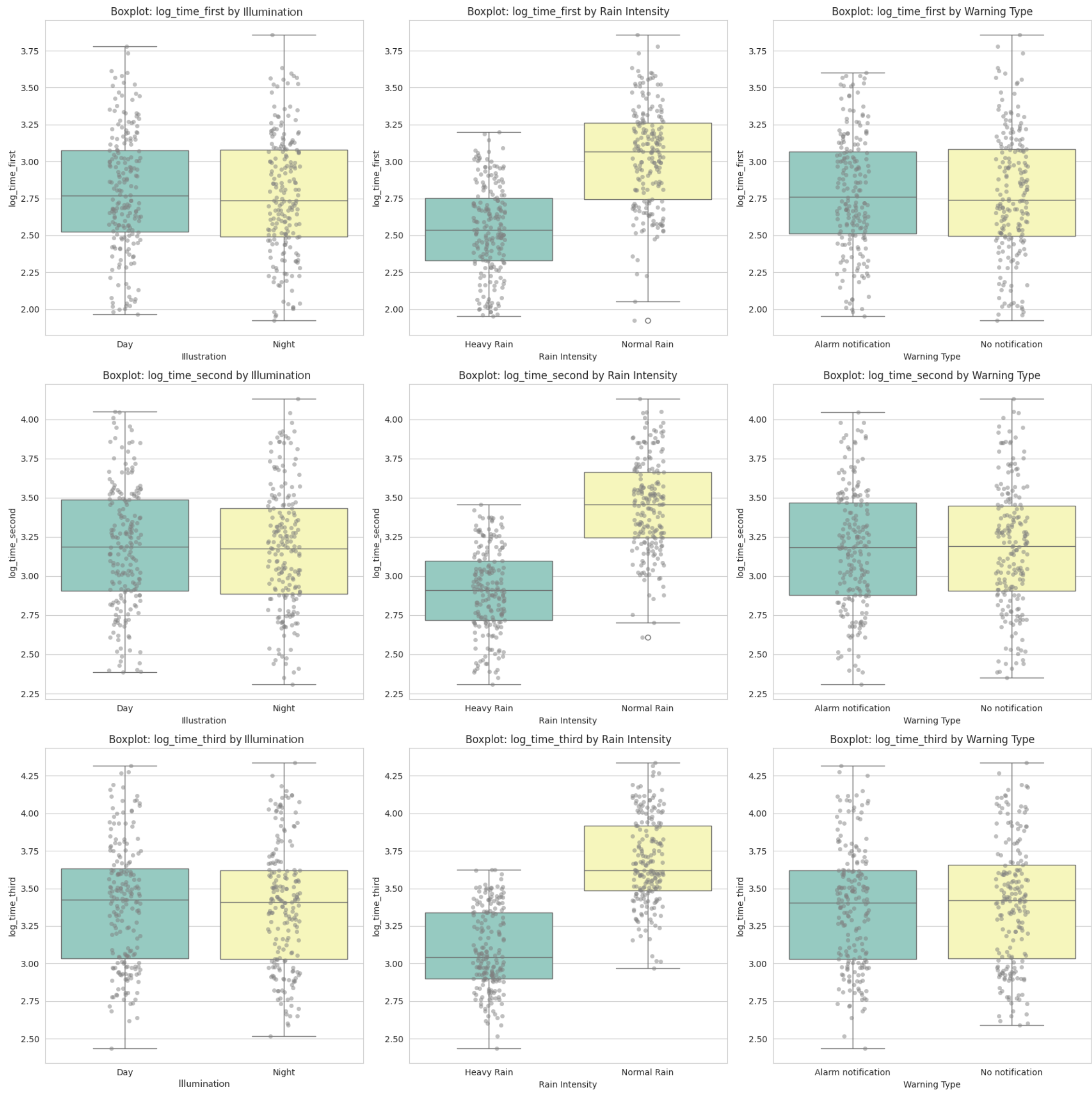


Figure 7: Boxplots of user responses for walk view

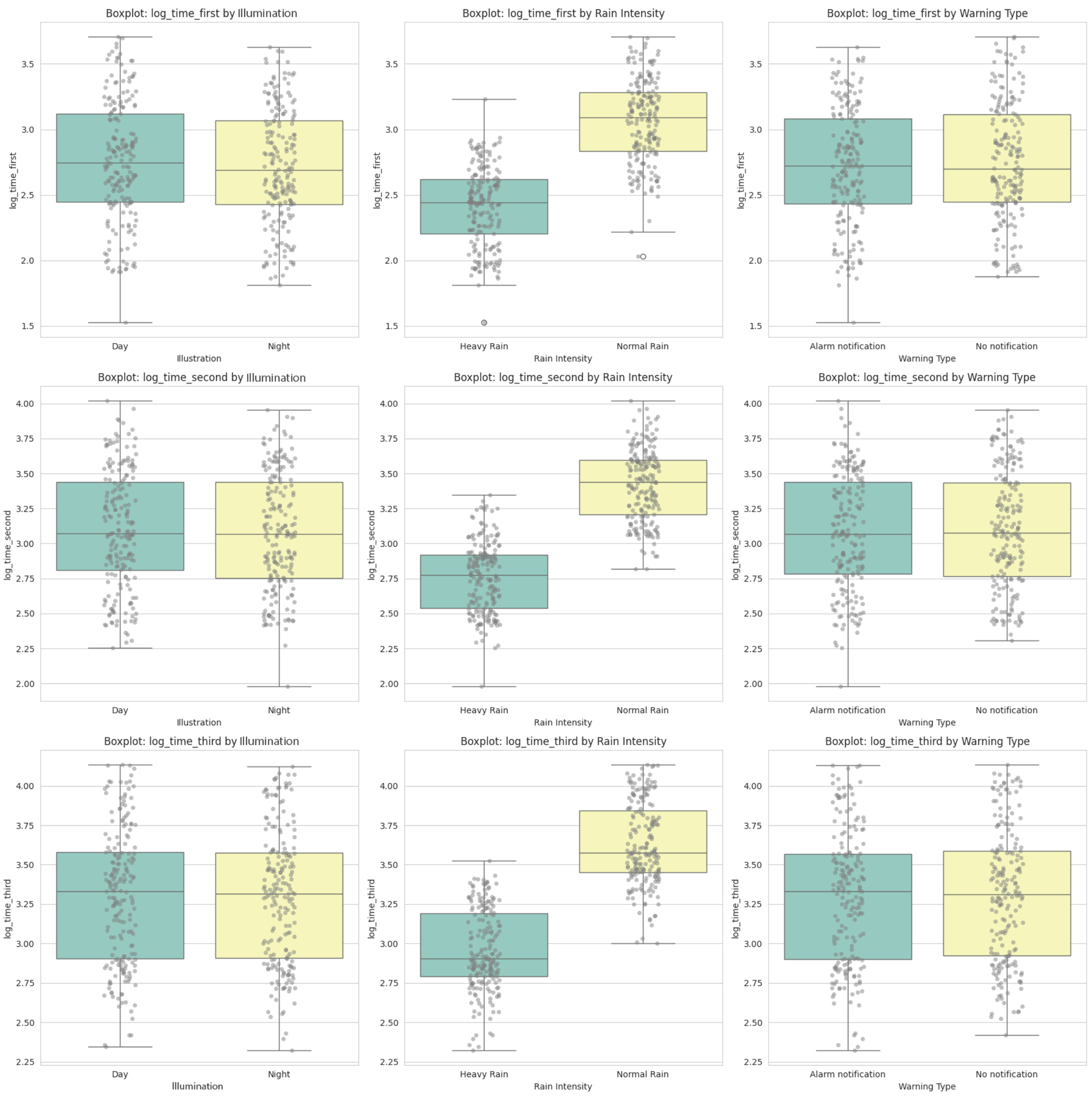


Figure 8: Boxplots of user responses for drive view

16 Appendix E: Complete Results of ANOVA

	F Value	Num DF	Den DF	$Pr > F$	Significance
Illumination	1.86	1.00	49.00	0.18	
Rain level	397.11	1.00	49.00	0.00	***
Warning	0.36	1.00	49.00	0.55	
Illumination:Rain level	3.30	1.00	49.00	0.08	
Illumination:Warning	0.48	1.00	49.00	0.49	
Rain level:Warning	1.02	1.00	49.00	0.32	
Illumination:Rain level:Warning	0.00	1.00	49.00	0.99	

Table 8: ANOVA result for the first time (log) in the walk view

	F Value	Num DF	Den DF	$Pr > F$	Significance
Illumination	0.46	1.00	49.00	0.50	
Rain level	635.65	1.00	49.00	0.00	***
Warning	0.69	1.00	49.00	0.41	
Illumination:Rain level	1.16	1.00	49.00	0.29	
Illumination:Warning	0.35	1.00	49.00	0.56	
Rain level:Warning	1.92	1.00	49.00	0.17	
Illumination:Rain level:Warning	0.44	1.00	49.00	0.51	

Table 9: ANOVA result for the second time (log) in the walk view

	F Value	Num DF	Den DF	$Pr > F$	Significance
Illumination	0.18	1.00	49.00	0.67	
Rain level	1407.54	1.00	49.00	0.00	***
Warning	2.89	1.00	49.00	0.10	
Illumination:Rain level	0.45	1.00	49.00	0.51	
Illumination:Warning	0.00	1.00	49.00	0.95	
Rain level:Warning	2.02	1.00	49.00	0.16	
Illumination:Rain level:Warning	0.19	1.00	49.00	0.66	

Table 10: ANOVA result for the third time (log) in the walk view

	F Value	Num DF	Den DF	$Pr > F$	Significance
Illumination	0.03	1.00	49.00	0.86	
Rain level	174.75	1.00	49.00	0.00	***
Warning	0.68	1.00	49.00	0.41	
Illumination:Rain level	0.90	1.00	49.00	0.35	
Illumination:Warning	0.08	1.00	49.00	0.77	
Rain level:Warning	1.23	1.00	49.00	0.27	
Illumination:Rain level:Warning	2.55	1.00	49.00	0.12	

Table 11: ANOVA result for the threat confirmation (log) in the walk view

	F Value	Num DF	Den DF	$Pr > F$	Significance
Illumination	0.10	1.00	49.00	0.75	
Rain level	219.83	1.00	49.00	0.00	***
Warning	1.02	1.00	49.00	0.32	
Illumination:Rain level	0.44	1.00	49.00	0.51	
Illumination:Warning	0.44	1.00	49.00	0.51	
Rain level:Warning	0.83	1.00	49.00	0.37	
Illumination:Rain level:Warning	0.64	1.00	49.00	0.43	

Table 12: ANOVA result for the motivation loss (log) in the walk view

	F Value	Num DF	Den DF	$Pr > F$	Significance
Illumination	0.08	1.00	49.00	0.78	
Rain level	730.46	1.00	49.00	0.00	***
Warning	1.19	1.00	49.00	0.28	
Illumination:Rain level	1.40	1.00	49.00	0.24	
Illumination:Warning	0.13	1.00	49.00	0.72	
Rain level:Warning	0.90	1.00	49.00	0.35	
Illumination:Rain level:Warning	0.09	1.00	49.00	0.77	

Table 13: ANOVA result for the risk tolerance (log) in the walk view

	F Value	Num DF	Den DF	$Pr > F$	Significance
Illumination	5.80	1.00	49.00	0.02	*
Rain level	1000.54	1.00	49.00	0.00	***
Warning	4.04	1.00	49.00	0.05	*
Illumination:Rain level	0.78	1.00	49.00	0.38	
Illumination:Warning	0.38	1.00	49.00	0.54	
Rain level:Warning	1.73	1.00	49.00	0.19	
Illumination:Rain level:Warning	1.34	1.00	49.00	0.25	

Table 14: ANOVA result for the first time (log) in the drive view

	F Value	Num DF	Den DF	$Pr > F$	Significance
Illumination	6.19	1.00	49.00	0.02	*
Rain level	4352.42	1.00	49.00	0.00	***
Warning	5.02	1.00	49.00	0.03	*
Illumination:Rain level	0.00	1.00	49.00	0.99	
Illumination:Warning	0.53	1.00	49.00	0.47	
Rain level:Warning	0.38	1.00	49.00	0.54	
Illumination:Rain level:Warning	0.26	1.00	49.00	0.61	

Table 15: ANOVA result for the second time (log) in the drive view

	F Value	Num DF	Den DF	$Pr > F$	Significance
Illumination	0.64	1.00	49.00	0.43	
Rain level	7184.94	1.00	49.00	0.00	***
Warning	7.42	1.00	49.00	0.01	**
Illumination:Rain level	0.85	1.00	49.00	0.36	
Illumination:Warning	0.94	1.00	49.00	0.34	
Rain level:Warning	1.08	1.00	49.00	0.30	
Illumination:Rain level:Warning	0.13	1.00	49.00	0.72	

Table 16: ANOVA result for the third time (log) in the drive view

	F Value	Num DF	Den DF	$Pr > F$	Significance
Illumination	0.46	1.00	49.00	0.50	
Rain level	551.64	1.00	49.00	0.00	***
Warning	0.08	1.00	49.00	0.78	
Illumination:Rain level	0.50	1.00	49.00	0.48	
Illumination:Warning	4.01	1.00	49.00	0.05	*
Rain level:Warning	2.90	1.00	49.00	0.10	
Illumination:Rain level:Warning	3.22	1.00	49.00	0.08	

Table 17: ANOVA result for the threat confirmation (log) in the drive view

	F Value	Num DF	Den DF	$Pr > F$	Significance
Illumination	2.21	1.00	49.00	0.14	
Rain level	759.55	1.00	49.00	0.00	***
Warning	0.96	1.00	49.00	0.33	
Illumination:Rain level	0.13	1.00	49.00	0.72	
Illumination:Warning	0.02	1.00	49.00	0.88	
Rain level:Warning	0.05	1.00	49.00	0.82	
Illumination:Rain level:Warning	0.01	1.00	49.00	0.93	

Table 18: ANOVA result for the motivation loss (log) in the drive view

	F Value	Num DF	Den DF	$Pr > F$	Significance
Illumination	2.42	1.00	49.00	0.13	
Rain level	1354.89	1.00	49.00	0.00	***
Warning	0.59	1.00	49.00	0.44	
Illumination:Rain level	0.59	1.00	49.00	0.45	
Illumination:Warning	1.67	1.00	49.00	0.20	
Rain level:Warning	3.06	1.00	49.00	0.09	
Illumination:Rain level:Warning	0.50	1.00	49.00	0.48	

Table 19: ANOVA result for the risk tolerance (log) in the drive view

17 Appendix F: Complete Results of Linear mixed-effect model

Fixed effects					
	Estimate	**Std. Error**	**df**	**t value**	**Pr($>|t|$)**
(Intercept)	4.08	1.18	34.41	3.46	0.00 **
Floor severity	0.07	0.09	34.00	0.82	0.42
Flood risk	0.03	0.08	34.00	0.41	0.68
Floor fear	-0.00	0.06	34.00	-0.01	0.99
Response efficacy	-0.03	0.09	34.00	-0.35	0.73
Self-efficacy	-0.22	0.09	34.00	-2.59	0.01 *
Response costs	0.04	0.07	34.00	0.52	0.61
Gender	0.03	0.11	34.00	0.25	0.80
Age	-0.09	0.06	34.00	-1.54	0.13
Education	0.09	0.06	34.00	1.42	0.17
Income	-0.04	0.02	34.00	-1.73	0.09
Flood experience	-0.01	0.06	34.00	-0.24	0.81
Trainings	-0.12	0.12	34.00	-1.01	0.32
Flood knowledge	0.06	0.07	34.00	0.89	0.38
Height	-0.00	0.01	34.00	-0.83	0.41
Sickness	0.02	0.02	34.00	0.79	0.43

Random effects			
Groups	**Name**	**Variance**	**Std. Dev.**
User ID	(Intercept)	0.07	0.27
Condition category	(Intercept)	0.07	0.26
Residual		0.03	0.17

Table 20: LMM result for the first time (log) in the walk view

Fixed effects					
	Estimate	**Std. Error**	**df**	**t value**	**Pr($>\|t\|$)**
(Intercept)	4.30	1.05	34.63	4.09	0.00 ***
Floor severity	0.06	0.08	34.00	0.78	0.44
Flood risk	0.04	0.07	34.00	0.57	0.57
Floor fear	-0.00	0.06	34.00	-0.01	1.00
Response efficacy	-0.05	0.08	34.00	-0.63	0.53
Self-efficacy	-0.17	0.08	34.00	-2.26	0.03 *
Response costs	0.01	0.06	34.00	0.10	0.92
Gender	0.05	0.10	34.00	0.55	0.59
Age	-0.02	0.05	34.00	-0.37	0.72
Education	-0.04	0.05	34.00	-0.72	0.48
Income	-0.04	0.02	34.00	-1.97	0.06
Flood experience	0.04	0.05	34.00	0.80	0.43
Trainings	-0.11	0.10	34.00	-1.05	0.30
Flood knowledge	0.07	0.06	34.00	1.07	0.29
Height	-0.00	0.01	34.00	-0.61	0.55
Sickness	0.02	0.02	34.00	0.75	0.46
Random effects					
Groups	**Name**	**Variance**	**Std. Dev.**		
User ID	(Intercept)	0.06	0.24		
Condition category	(Intercept)	0.08	0.29		
Residual		0.02	0.13		

Table 21: LMM result for the second time (log) in the walk view

Fixed effects					
	Estimate	**Std. Error**	**df**	**t value**	**Pr($>\|t\|$)**
(Intercept)	4.95	1.06	34.75	4.68	0.00 ***
Floor severity	0.06	0.08	34.00	0.70	0.49
Flood risk	0.04	0.07	34.00	0.62	0.54
Floor fear	-0.01	0.06	34.00	-0.16	0.87
Response efficacy	-0.08	0.08	34.00	-1.02	0.32
Self-efficacy	-0.16	0.08	34.00	-2.11	0.04 *
Response costs	0.02	0.06	34.00	0.25	0.80
Gender	0.05	0.10	34.00	0.51	0.62
Age	-0.01	0.05	34.00	-0.15	0.88
Education	-0.07	0.06	34.00	-1.23	0.23
Income	-0.05	0.02	34.00	-2.40	0.02 *
Flood experience	0.03	0.05	34.00	0.51	0.61
Trainings	-0.12	0.10	34.00	-1.15	0.26
Flood knowledge	0.06	0.06	34.00	0.87	0.39
Height	-0.00	0.01	34.00	-0.65	0.52
Sickness	0.02	0.02	34.00	0.87	0.39

Random effects			
Groups	**Name**	**Variance**	**Std. Dev.**
User ID	(Intercept)	0.06	0.25
Condition category	(Intercept)	0.10	0.32
Residual		0.01	0.11

Table 22: LMM result for the third time (log) in the walk view

Fixed effects					
	Estimate	**Std. Error**	**df**	**t value**	**Pr($>|t|$)**
(Intercept)	3.25	2.06	34.13	1.57	0.13
Floor severity	0.10	0.16	34.00	0.61	0.54
Flood risk	0.04	0.14	34.00	0.30	0.76
Floor fear	-0.06	0.11	34.00	-0.56	0.58
Response efficacy	-0.08	0.16	34.00	-0.48	0.64
Self-efficacy	-0.16	0.15	34.00	-1.08	0.29
Response costs	0.02	0.12	34.00	0.12	0.90
Gender	0.19	0.19	34.00	0.99	0.33
Age	0.09	0.11	34.00	0.89	0.38
Education	-0.17	0.11	34.00	-1.55	0.13
Income	-0.09	0.04	34.00	-2.15	0.04 *
Flood experience	0.16	0.11	34.00	1.51	0.14
Trainings	-0.08	0.20	34.00	-0.37	0.72
Flood knowledge	0.09	0.12	34.00	0.76	0.46
Height	-0.00	0.01	34.00	-0.22	0.83
Sickness	0.01	0.04	34.00	0.12	0.90

Random effects			
Groups	**Name**	**Variance**	**Std. Dev.**
User ID	(Intercept)	0.23	0.48
Condition category	(Intercept)	0.07	0.26
Residual		0.08	0.29

Table 23: LMM result for the threat confirmation (log) in the walk view

Fixed effects					
	Estimate	**Std. Error**	**df**	**t value**	**Pr($>|t|$)**
(Intercept)	6.06	2.16	34.20	2.80	0.01 **
Floor severity	0.07	0.16	34.00	0.43	0.67
Flood risk	0.02	0.15	34.00	0.14	0.89
Floor fear	-0.04	0.12	34.00	-0.35	0.73
Response efficacy	-0.25	0.17	34.00	-1.45	0.16
Self-efficacy	-0.17	0.16	34.00	-1.09	0.28
Response costs	0.06	0.13	34.00	0.45	0.65
Gender	0.07	0.20	34.00	0.34	0.73
Age	0.07	0.11	34.00	0.63	0.53
Education	-0.18	0.11	34.00	-1.62	0.12
Income	-0.14	0.04	34.00	-3.35	0.00 **
Flood experience	-0.04	0.11	34.00	-0.37	0.71
Trainings	-0.19	0.21	34.00	-0.90	0.37
Flood knowledge	0.02	0.13	34.00	0.18	0.85
Height	-0.00	0.01	34.00	-0.29	0.77
Sickness	0.03	0.04	34.00	0.63	0.53
Random effects					
Groups	**Name**	**Variance**	**Std. Dev.**		
User ID	(Intercept)	0.25	0.50		
Condition category	(Intercept)	0.11	0.33		
Residual		0.11	0.33		

Table 24: LMM result for the motivation loss (log) in the walk view

Fixed effects					
	Estimate	**Std. Error**	**df**	**t value**	**Pr($>\|t\|$)**
(Intercept)	4.60	1.62	34.33	2.84	0.01 **
Floor severity	0.06	0.12	34.00	0.52	0.61
Flood risk	0.04	0.11	34.00	0.35	0.73
Floor fear	-0.05	0.09	34.00	-0.59	0.56
Response efficacy	-0.11	0.13	34.00	-0.85	0.40
Self-efficacy	-0.14	0.12	34.00	-1.22	0.23
Response costs	0.00	0.10	34.00	0.03	0.98
Gender	0.12	0.15	34.00	0.81	0.42
Age	0.07	0.08	34.00	0.85	0.40
Education	-0.15	0.08	34.00	-1.80	0.08
Income	-0.09	0.03	34.00	-2.76	0.01 **
Flood experience	0.08	0.08	34.00	0.92	0.36
Trainings	-0.10	0.16	34.00	-0.60	0.55
Flood knowledge	0.05	0.10	34.00	0.56	0.58
Height	-0.00	0.01	34.00	-0.28	0.78
Sickness	0.01	0.03	34.00	0.27	0.79

Random effects			
Groups	**Name**	**Variance**	**Std. Dev.**
User ID	(Intercept)	0.14	0.38
Condition category	(Intercept)	0.10	0.32
Residual		0.04	0.20

Table 25: LMM result for the risk tolerance (log) in the walk view

Fixed effects					
	Estimate	**Std. Error**	**df**	**t value**	**Pr($> \|t\|$)**
(Intercept)	3.74	1.15	33.74	3.25	0.00 **
Floor severity	-0.00	0.08	33.00	-0.05	0.96
Flood risk	-0.04	0.08	33.00	-0.58	0.56
Floor fear	0.05	0.06	33.00	0.80	0.43
Response efficacy	0.02	0.08	33.00	0.27	0.79
Self-efficacy	-0.25	0.09	33.00	-2.77	0.01 **
Response costs	-0.02	0.08	33.00	-0.20	0.84
Gender	0.07	0.10	33.00	0.71	0.48
Age	-0.12	0.06	33.00	-2.04	0.05 *
Education	0.08	0.06	33.00	1.45	0.16
Income	-0.05	0.02	33.00	-2.25	0.03 *
Flood experience	0.00	0.06	33.00	0.06	0.95
Trainings	-0.10	0.13	33.00	-0.79	0.44
Flood knowledge	0.09	0.07	33.00	1.39	0.17
Height	-0.00	0.01	33.00	-0.43	0.67
Sickness	0.01	0.02	33.00	0.23	0.82
Drive ability	0.11	0.07	33.00	1.50	0.14
Random effects					
Groups	**Name**	**Variance**	**Std. Dev.**		
User ID	(Intercept)	0.06	0.25		
Condition category	(Intercept)	0.12	0.35		
Residual		0.03	0.16		

Table 26: LMM result for the first time (log) in the drive view

Fixed effects					
	Estimate	**Std. Error**	**df**	**t value**	**Pr($>|t|$)**
(Intercept)	3.76	1.06	33.90	3.54	0.00 **
Floor severity	0.00	0.07	33.00	0.02	0.98
Flood risk	-0.03	0.07	33.00	-0.48	0.64
Floor fear	0.05	0.06	33.00	0.97	0.34
Response efficacy	0.02	0.08	33.00	0.33	0.74
Self-efficacy	-0.18	0.08	33.00	-2.16	0.04 *
Response costs	-0.03	0.07	33.00	-0.50	0.62
Gender	0.11	0.09	33.00	1.19	0.24
Age	-0.05	0.06	33.00	-0.81	0.42
Education	-0.05	0.05	33.00	-0.99	0.33
Income	-0.05	0.02	33.00	-2.35	0.02 *
Flood experience	0.03	0.05	33.00	0.47	0.64
Trainings	-0.12	0.12	33.00	-1.04	0.31
Flood knowledge	0.07	0.06	33.00	1.10	0.28
Height	0.00	0.00	33.00	0.04	0.97
Sickness	0.01	0.02	33.00	0.53	0.60
Drive ability	0.11	0.07	33.00	1.66	0.11

Random effects			
Groups	**Name**	**Variance**	**Std. Dev.**
User ID	(Intercept)	0.06	0.24
Condition category	(Intercept)	0.12	0.35
Residual		0.01	0.09

Table 27: LMM result for the second time (log) in the drive view

Fixed effects					
	Estimate	**Std. Error**	**df**	**t value**	**Pr($>|t|$)**
(Intercept)	4.39	1.11	33.85	3.95	0.00 ***
Floor severity	-0.02	0.08	33.00	-0.25	0.80
Flood risk	-0.03	0.07	33.00	-0.36	0.72
Floor fear	0.04	0.06	33.00	0.62	0.54
Response efficacy	0.01	0.08	33.00	0.16	0.87
Self-efficacy	-0.14	0.09	33.00	-1.57	0.13
Response costs	-0.02	0.07	33.00	-0.24	0.81
Gender	0.10	0.10	33.00	0.98	0.34
Age	-0.03	0.06	33.00	-0.49	0.63
Education	-0.08	0.05	33.00	-1.54	0.13
Income	-0.06	0.02	33.00	-2.58	0.01 *
Flood experience	0.03	0.06	33.00	0.55	0.59
Trainings	-0.09	0.12	33.00	-0.69	0.49
Flood knowledge	0.05	0.06	33.00	0.76	0.45
Height	-0.00	0.01	33.00	-0.29	0.77
Sickness	-0.00	0.02	33.00	-0.07	0.94
Drive ability	0.11	0.07	33.00	1.54	0.13
Random effects					
Groups	**Name**	**Variance**	**Std. Dev.**		
User ID	(Intercept)	0.06	0.25		
Condition category	(Intercept)	0.13	0.36		
Residual		0.01	0.07		

Table 28: LMM result for the third time (log) in the drive view

Fixed effects					
	Estimate	**Std. Error**	**df**	**t value**	**Pr($>|t|$)**
(Intercept)	2.91	2.30	33.17	1.26	0.22
Floor severity	0.03	0.16	33.00	0.18	0.86
Flood risk	-0.10	0.15	33.00	-0.63	0.53
Floor fear	0.03	0.12	33.00	0.29	0.77
Response efficacy	-0.00	0.16	33.00	-0.03	0.98
Self-efficacy	-0.17	0.18	33.00	-0.93	0.36
Response costs	-0.07	0.15	33.00	-0.43	0.67
Gender	0.32	0.20	33.00	1.56	0.13
Age	0.06	0.12	33.00	0.47	0.64
Education	-0.24	0.11	33.00	-2.13	0.04 *
Income	-0.09	0.04	33.00	-2.06	0.05 *
Flood experience	0.09	0.12	33.00	0.79	0.44
Trainings	-0.15	0.26	33.00	-0.59	0.56
Flood knowledge	0.08	0.13	33.00	0.60	0.55
Height	0.00	0.01	33.00	0.38	0.71
Sickness	0.01	0.05	33.00	0.29	0.77
Drive ability	0.12	0.14	33.00	0.81	0.42
Random effects					
Groups	**Name**	**Variance**	**Std. Dev.**		
User ID	(Intercept)	0.26	0.51		
Condition category	(Intercept)	0.11	0.33		
Residual		0.06	0.25		

Table 29: LMM result for the threat confirmation (log) in the drive view

Fixed effects					
	Estimate	**Std. Error**	**df**	**t value**	**Pr($>\|t\|$)**
(Intercept)	6.01	2.78	33.13	2.16	0.04 *
Floor severity	-0.05	0.20	33.00	-0.23	0.82
Flood risk	-0.11	0.18	33.00	-0.61	0.55
Floor fear	0.06	0.15	33.00	0.40	0.69
Response efficacy	-0.10	0.20	33.00	-0.50	0.62
Self-efficacy	-0.11	0.22	33.00	-0.49	0.63
Response costs	0.07	0.18	33.00	0.39	0.70
Gender	0.09	0.25	33.00	0.38	0.70
Age	0.03	0.15	33.00	0.18	0.86
Education	-0.28	0.14	33.00	-2.02	0.05
Income	-0.15	0.05	33.00	-2.76	0.01 **
Flood experience	-0.00	0.15	33.00	-0.03	0.98
Trainings	-0.17	0.31	33.00	-0.54	0.59
Flood knowledge	-0.02	0.16	33.00	-0.13	0.89
Height	-0.00	0.01	33.00	-0.23	0.82
Sickness	-0.03	0.06	33.00	-0.54	0.60
Drive ability	0.13	0.17	33.00	0.75	0.46

Random effects			
Groups	**Name**	**Variance**	**Std. Dev.**
User ID	(Intercept)	0.39	0.62
Condition category	(Intercept)	0.12	0.35
Residual		0.06	0.25

Table 30: LMM result for the motivation loss (log) in the drive view

Fixed effects					
	Estimate	**Std. Error**	**df**	**t value**	**Pr($> \|t\|$)**
(Intercept)	3.94	1.96	33.27	2.01	0.05
Floor severity	0.00	0.14	33.00	0.03	0.98
Flood risk	-0.08	0.13	33.00	-0.60	0.55
Floor fear	0.01	0.10	33.00	0.06	0.95
Response efficacy	-0.01	0.14	33.00	-0.07	0.95
Self-efficacy	-0.10	0.16	33.00	-0.65	0.52
Response costs	-0.02	0.13	33.00	-0.14	0.89
Gender	0.21	0.17	33.00	1.20	0.24
Age	0.06	0.10	33.00	0.54	0.60
Education	-0.22	0.10	33.00	-2.24	0.03 *
Income	-0.09	0.04	33.00	-2.43	0.02 *
Flood experience	0.09	0.10	33.00	0.84	0.41
Trainings	-0.07	0.22	33.00	-0.30	0.76
Flood knowledge	0.02	0.11	33.00	0.14	0.89
Height	0.00	0.01	33.00	0.12	0.91
Sickness	-0.01	0.04	33.00	-0.32	0.75
Drive ability	0.09	0.12	33.00	0.74	0.46

Random effects			
Groups	**Name**	**Variance**	**Std. Dev.**
User ID	(Intercept)	0.19	0.44
Condition category	(Intercept)	0.13	0.36
Residual		0.03	0.17

Table 31: LMM result for the risk tolerance (log) in the drive view