Drivers of Household Risk Perceptions and Adjustment Intentions to Tornado Hazards in Oklahoma

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ABSTRACT

Tornadoes are responsible for considerable property damage and loss of life across the state of Oklahoma. While several studies have explored drivers of tornado adjustment behaviors, their results are not consistent in terms of their significance and direction. To address this shortcoming in the literature, we surveyed households using a disproportionate stratified sampling procedure from counties in Oklahoma that frequently experience tornado threats to explore drivers of adjustments. We used Structural Equation Modeling (SEM) to explore relationships among variables highlighted in the Protection Motivation Theory (PMT) and related literature that affect adjustment intentions and risk perceptions. Overall, we found the factors highlighted in the PMT are effective at predicting households' intentions of adopting adjustment behaviors associated with tornado hazards. Threat appraisals, however, were less important than coping appraisals in predicting tornado hazard adjustment intentions. In further analysis, we grouped adjustments as 1) basic (e.g., flashlight, food and water supply) and 2) complex (e.g., insurance, storm shelter), and found that while coping appraisals are significant drivers of both adjustment categories, the effect of threat appraisals is only significant for complex adjustment intentions. We also found that emotional responses to hazards are major drivers of threat appraisals, stronger than perceived knowledge and hazard salience. Moreover, we found that demographic characteristics affect both adjustment intentions and threat appraisals. The additions to the PMT and categorization of adjustment activities improve our understanding of the PMT in different contexts. Such insights provide scholars and emergency managers with strategies for risk communication efforts.

Significance Statement

Tornadoes have caused considerable property damage and loss of life across the state of Oklahoma. Here, we utilize the Protection Motivation Theory (PMT) to explore drivers of tornado hazard adjustment intentions by surveying households from counties in Oklahoma that frequently experience tornadoes. Overall, we found that threat appraisals and coping appraisals produce differential effects depending on the type of hazard adjustment in question. Our findings show that risk perceptions are not a significant predictor of basic adjustments (e.g., flashlight, food and water supply), but are a significant predictor of complex adjustments (e.g., insurance, storm shelter). Future work should provide broader perspectives on how to advance the PMT to better predict adjustment intentions for various hazards.

1. Introduction

Approximately 1,200 tornadoes affect the U.S. in a given year (The NOAA National Severe Storms Laboratory, n.d.). While many of these tornadoes are relatively weak or affect uninhabited areas, a number do strike inhabited areas annually, leading to considerable property damage and loss of life. Oklahoma, located within what is referred to as tornado alley, experiences an average of 57 tornadoes per year and has sustained substantial tornado damage in the past (US Department of Commerce, n.d.-a). The state has documented over 340 deaths and billions in damages due to tornadoes since 1950 (Hall 2021). These large-scale events include the 1999 Bridge-Creek Moore tornado that resulted in 36 fatalities and an estimated $1 billion in damages and the Moore tornado of 2013 which resulted in 24 deaths and an estimated $2 billion in damages (US Department of Commerce, n.d.-b; n.d.-c).

While governments can raise awareness of risks and provide incentives for risk reduction behaviors, many preparedness and mitigation measures, referred to here as hazard adjustments, are ultimately up to households to decide to adopt (Buchenrieder et al. 2021; Hudson et al. 2020). In the case of tornadoes, households have several adjustments they can undertake, such as developing a family plan, keeping three days of food and water on hand, and installing a storm shelter. Survey research conducted by FEMA in 2020, however, shows that households are not adopting many adjustment measures for hazards (FEMA 2020). Research related to tornadoes has largely focused on the response phase, namely, whether individuals understand and respond to imminent threat warning messages (Ash et al. 2020; Jon et al. 2019; Strader et al. 2019; Strader et al. 2021). Comparatively fewer studies have explored drivers of preparedness and mitigation measures in response to risks associated with tornadoes (Choi and Wehde 2020; Choi et al. 2020; Simms et al. 2013). These studies have typically relied upon simple correlations to explore drivers of adjustments and explored intention to adjust as a unidimensional concept (i.e. intention to undertake a suite of adjustments) or as a discrete set of decisions (i.e. intention to develop a family plan, purchase insurance, etc.). Recent research indicates that adjustments could be treated as multidimensional and that more rigorous analytical approaches, such as Structural Equation Modeling (SEM), are required to fully understand the relationships among adjustment measures (Huntsman et al. 2021).

To address these shortcomings in the literature, we deployed a disproportionately sampled, mail-based survey across the state of Oklahoma. Building off previous work by the authors with a student sample (Huntsman et al. 2021) and the theoretical foundation provided by the Protection Motivation Theory (PMT) (Rogers 1975), we collected data to capture the drivers of adjustment decision-making among households in response to risks associated with tornadoes. Our aim with this research is threefold. First, by using factor analysis, we explore ways to categorize adjustments measures to provide insights on the characteristics of suites of adjustment options. Second, we use SEM's standardized coefficient estimates to understand the relative importance of various factors identified in previous literature in relation to specific adjustment measures. Third, starting with the foundation provided by the PMT, we explore additional factors suggested by the literature to affect adjustment intentions to build models with more explanatory power.

2. Literature Review

a. Protection Motivation Theory (PMT)

The PMT was originally developed in 1975 to explain health-related risky behaviors such as cigarette smoking (Milne et al. 2000; Rogers and Prentice-Dunn 1997). In recent years, disaster scholars have been using PMT to explain hazard adjustment intentions and behaviors (Botzen et al. 2019; Budhathoki et al. 2020; Greer et al. 2020; Poussin et al. 2014; Seebauer and Babcicky 2020; Tang and Feng 2018; H. -C. Wu et al. 2017). Compared to the Theory of Reasoned Action (Fishbein and Ajzen 1975), the Theory of Planning Behavior (Fishbein and Ajzen 2011), Person-Relative-to-Event Theory (Mulilis and Duval 1995), and the Protective Action Decision Model (Lindell 2018), PMT provides a relatively simple paradigm that can be used to examine attitudes towards different types of protective actions in varying contexts. Based on the PMT, threat appraisals and coping appraisals drive individuals' decisions to adopt protective actions (Heidenreich, Masson, and Bamberg 2020). In the hazard adjustment literature, protective actions can be seen as the adjustments that people adopt to prepare for disasters or mitigate hazard risks (Greer et al. 2020; Lindell et al. 2009; Lindell and Perry 2000; Perry and Lindell 2008). Threat appraisal, also referred to as "risk perception" (Bubeck et al. 2012; Grothmann and Reusswig 2006), consists of perceived probability or consequences that relate to a certain hazard. Coping appraisals are comprised of response efficacy, self-efficacy, and response cost. Response efficacy measures the perceived effectiveness of a given hazard adjustment; self-efficacy measures the perceived ease of adopting a given hazard adjustment; finally, response cost measures the financial investment required for a given hazard adjustment (Floyed et al. 2000; Rogers 1975; Rogers and Prentice-Dunn 1997). The PMT has gained popularity in explaining protective actions in response to COVID-19 (Kim and Crimmins 2020; P. W. Wang et al. 2021; Rather 2021; Al-Rasheed 2020), online security behavior of internet users (Menard et al. 2017; Menard et al. 2018; Van Bavel et al. 2019) and disaster risk mitigation behaviors (Becker et al. 2017; Bubeck et al. 2012; Budhathoki et al. 2020; Gebrehiwot and Van Der Veen 2015; Keshavarz and Karami 2016; Van Der Veen 2015; Vinnell et al. 2020).

PMT explains how threat and coping appraisals change attitudes, which subsequently affect hazard adjustments (Rogers 1975). Threat appraisal is generally measured by asking study participants to report the perceived probability of a disaster event happening (H. -C. Wu et al. 2014) or the perceived likelihood of impacts that a household or a community would experience during a given disaster (Greer et al. 2020). When individuals perceive the threat (risk) is high, they move into a stage where they decide if they should make possible adjustments to the risk and consider their adjustment options. In this stage, they consider the characteristics (coping appraisals) of each adjustment option, such as how effective it would be at reducing risk and the cost associated with adopting said adjustment, before deciding how to adjust. Maddux & Rogers (1983) suggests that the interaction of threat and coping appraisals plays an important role in predicting individuals' adoption of hazard adjustment behaviors. This effect is realized through an intermediary variable, which is referred to as "protection motivation". More specifically, high levels of threat appraisal and coping appraisals can stimulate the adoption of hazard adjustment behaviors. In contrast, a high level of threat appraisal and a low level of coping appraisal typically leads to a lower likelihood of adopting hazard adjustment behaviors, often referred to as avoidance behaviors (Pepitone and Festinger 1959). If threat appraisal is low, adjustments are not undertaken because individuals never move to a stage where they consider adjustments (Bockarjova and Steg 2014).

Rogers (1975) suggested that environmental, cognitive, and other factors can be incorporated into the PMT model to improve its explanatory power. There have been multiple attempts in the literature to expand the original PMT to account for additional factors and to apply the model in different scenarios (Azizam et al. 2020; Li et al. 2022; Y. Wang et al. 2019; D. Wu 2020; Ong et al. 2021). For example, Li et al. (2022) used qualitative characteristics of a hazard and hazard salience (driven by disaster experience) to predict risk perception. In addition, the authors added a multi-use variable to the model as one of the coping appraisal variables and used demographic variables to explain the variation of adjustment intentions (see Figure 1). Likewise, additional literature suggests that variables such as qualitative characteristics of hazards (Becker et al. 2012; Bubeck et al. 2012; Fischhoff et al. 1978; Lindell et al. 2015; Peacock et al. 2005; Rohli et al. 2018; Slovic 1987; Slovic et al. 2004; Terpstra 2011; Wachinger et al. 2013), disaster experience (Thistlethwaite et al. 2018; Wachinger et al. 2013), and hazard salience (Burger and Palmer 1992; Prater and Lindell 2000) affect threat appraisal. Other studies have added variables to coping appraisals, such as whether a given adjustment is useful for other purposes (Li et al. 2022; Lindell and Prater 2002). While the results are mixed, several studies suggest that demographic variables affect earthquake hazard adjustment intention directly (Botzen and Van Den Bergh 2012; Duží et al. 2017; Grothmann and Reusswig 2006; Harries and Penning-Rowsell 2011; Kellens et al. 2011; Lindell and Hwang 2008; Li et al. 2022; Prater and Lindell 2000; Qasim et al. 2015; Stojanov et al. 2015; Thistlethwaite et al. 2018; Zaalberg et al. 2009).

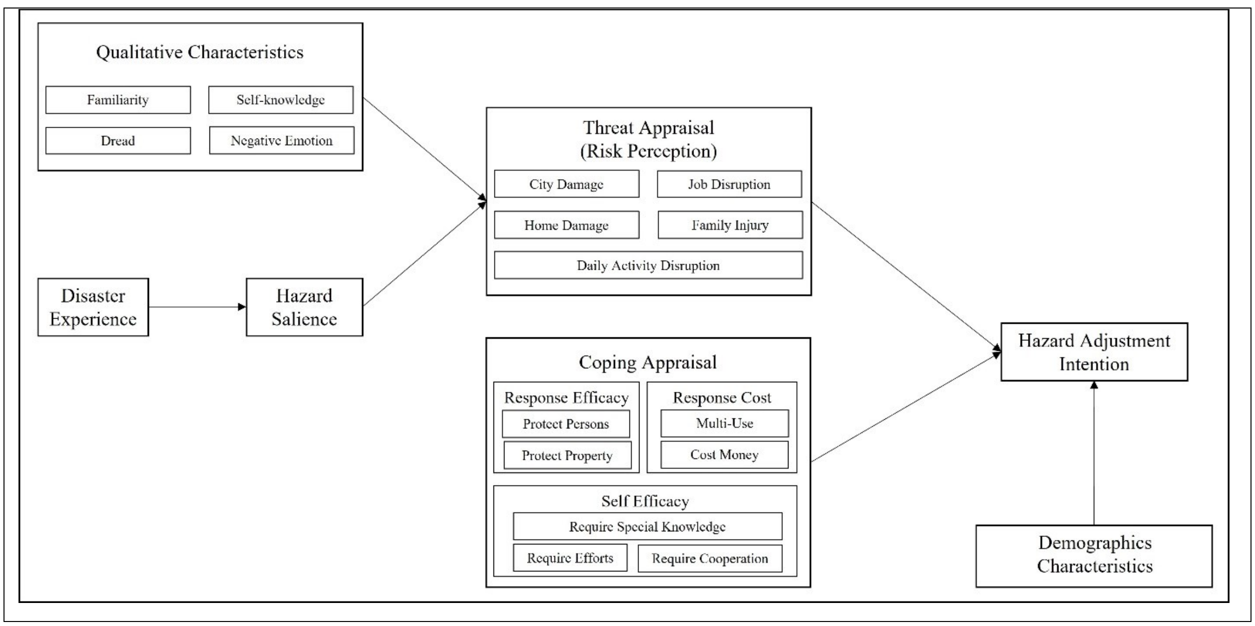

Figure 1: Li et al. (2022) Conceptual Model

b. Threat Appraisal (Risk Perception) Drivers

A number of studies have explored how individuals form risk perceptions. In the world of financial investment, Slovic et al. found that self-knowledge increases risk perceptions (Slovic et al. 2004). Disaster studies also found that perceived self-knowledge of natural hazards increases risk perceptions (Iorfa et al. 2020; Lindell et al. 2015; Peacock et al. 2005; Rohli et al. 2018; Wachinger et al. 2013). Studies also suggest familiarity affects risk perception (Li, Greer, and Wu

2022). Dread, a feeling associated with a lack of control and potentially fatal consequences (Slovic 1987), has been found to increase risk perceptions (Terpstra 2011; Becker et al. 2012; Fischhoff et al. 1978).

While negative emotions, such as fear and anger, are discussed in some PMT literature as a subcomponent of threat appraisal (Bubeck et al. 2012), many psychology and risk studies have suggested negative emotions are drivers of risk perception. Earlier studies suggest that negative emotions (negative affect) guides cognitive risk perceptions (Zajonc 1980, 1984). Additional experimental and clinical research also suggests that risk perception judgements are guided by negative emotions (Dohle, Keller, and Siegrist 2010; Finucane et al. 2000; Johnson and Tversky 1983; Slovic et al. 2007). While some studies identified fear as a driver for hazard adjustment (Kievik and Gutteling 2011; Terpstra 2011), other work found an indirect effect of fear on intentions to adopt hazard adjustment behaviors through risk perceptions (Finucane et al. 2000; Zaalberg et al. 2009). Some studies also suggest negative emotion affects risk perceptions directly (Lerner and Keltner 2001, 2010).

Previous studies have shown that direct and indirect disaster experience leads to higher levels of risk perceptions (Thistlethwaite et al. 2018; Wachinger et al. 2013). In general, research suggests that prior experience shapes how individuals perceive and respond to a threat (Bubeck et al., 2012), and prior experience with disasters and their impacts is an important determinant of risk perception (Lindell & Perry, 2012). In a flood mitigation survey of six European countries, Bradford et al. (2012) found that risk perceptions are usually low if the area is rarely plagued by disasters. As for the hazard salience, or how much someone thinks about a hazard, Prater and Lindell (2000) found that salience was correlated with risk perceptions. Burger and Palmer (1992) suggests that hazard salience drives risk perceptions in predicting adjustment intentions. Additionally, previous studies have found hazard salience is correlated with individuals' disaster experience (Pennebaker and Harber 1993; Perry and Lindell 1990). Moreover, hazard salience may act as a mediating variable between disaster experience and risk perceptions (Lindell and Hwang 2008; Li et al. 2022).

The effects of demographic variables on risk perceptions and adjustments are not conclusive. While several studies have found demographic variables such as ethnicity (Olofsson and Rashid 2011), homeownership (Greer, Wu, and Murphy 2018), and gender (Ho et al. 2008; Prater and Lindell 2000) are correlated with risk perceptions, other work suggested demographics characteristics have little to no correlations with risk perceptions (Bradford et al. 2012; Ho et al. 2008; Hudson, Hagedoorn, and Bubeck 2020; Huntsman et al. 2021; Li et al. 2022). Regarding socio-cultural context, the "white-male effect" is known for explaining the fact that while males have lower perceptions of various risks than women and minority groups therefore less likely to adopt hazard adjustment activities. Kahan et al. (2007) proposed the "identity-protective cognition", which suggests that people selectively trust and dismiss threats in a way that supports their cultural identity, the dynamic of which drives the white-male effect. In addition, previous studies also found that demographic variables directly predict adjustment behaviors. For example, some research has found that education level has shown limited to no influence on hazard adjustments (Botzen and Van Den Bergh 2012; Grothmann and Reusswig 2006; Lindell and Hwang 2008; Zaalberg et al. 2009), while others find a significant correlation between education and hazard adjustment (e.g., Qasim et al. 2015). While several prior studies have shown homeownership has a positive influence on hazard adjustment activities (Harries and Penning-Rowsell 2011; Thistlethwaite et al. 2018; Grothmann and Reusswig 2006), studies such as Kellens et al. (2011) show no such relationship exists between homeownership and flood mitigation strategies. Some studies suggest married couples and households with dependents are more likely to adjust for hazards (Duží et al. 2017; Kellens et al. 2011; Prater and Lindell 2000; Russell et al. 1995; Stojanov et al. 2015), while other studies did not find a significant effect of these variables on hazard adjustments (e.g., Qasim et al. 2015). Where some studies find that income level is strongly correlated with hazard adjustment behaviors (Grothmann and Reusswig 2006; Stojanov et al. 2015; Thistlethwaite et al. 2018), other studies did not find a significant relationship between income and hazard adjustment activities (Lindell and Hwang 2008; Zaalberg et al. 2009).

c. Coping Appraisals

While the PMT generally conceptualizes coping appraisals as the sum of response efficacy and self-efficacy appraisals, minus any costs of adopting the adjustment activity, several studies incorporate a multiuse variable in the response cost category (Lindell and Prater 2022; Lindell and Perry 2000; Huntsman et al. 2021; Greer et al. 2020; Li et al. 2022). This captures whether a hazard adjustment behavior could be used to mitigate other hazard risks or prepare for other disasters (e.g., Lindell and Whitney 2000); conceptually reducing the overall household hazard-adjustment-related investments in risk reduction measures. Studies suggest this multiuse variable encourages the intention of hazard adjustment adoption (Lindell and Prater 2002; Lindell and Perry 2000).

Studies on earthquake and tornado hazard adjustment suggest multiuse is either highly correlated with hazard adjustment intention or the most significant predictor of hazard adjustment models (Lindell and Prater 2002; Lindell and Perry 2000; H. -C. Wu et al. 2017; Huntsman et al. 2021; Greer et al. 2020).

This study builds on existing literature and two of our recent studies. Here, we use SEM to explore household-level tornado hazard adjustment intentions using the PMT and additional variables identified in the literature and our prior work on earthquakes. In recent years, SEM has shown promise in analyzing the interplay among the PMT components due to its ability to uncover linkages between PMT components (Blanthorne, Jones-Farmer, and Almer 2006; Nguyen et al. 2021). We argue that SEM will help clarify results, such as the mixed results of demographic variables we discussed earlier, among studies that have tried to introduce different variables to study hazard adjustment behaviors. While many studies apply regression analyses to predict adjustment intentions (e.g., Lindell and Hwang 2008; Botzen et al. 2019), regressions do not allow for multiple dependent variables in the same model. SEM overcomes this limitation by allowing us to specify different causal paths for all the variables in a single model. SEM has another major advantage over multiple regression because the former takes measurement error into account (Mackenzie, 2001). Measurement error can artificially diminish estimated slopes between the predictor and outcome variable, threatening the validity of findings. Using multivariate statistics (Qasim et al. 2015) or ANOVA (Bradford et al. 2012) in the comparisons between different demographic groups, few studies compare the effects of demographic variables on both PMT components and adjustment intentions.

Babcicky and Seebauer (2019) suggests conflicting results are a product of methodological weaknesses, including the failure to address all the PMT components, widely used conjoint measures that do not allow testing PMT components individually, the dichotomization of protective responses, and the inherent limitations of regression analysis. In this study, we attempt to overcome these challenges by incorporating extensive PMT components, relevant antecedents of risk perceptions, and demographic variables into one SEM model, allowing variables to be both independent and dependent variables in the same SEM model, reflecting measurement models and regression paths at the same time, and creating both individual SEM models for each adjustment intention and grouped SEM models for grouped adjustment intentions. Li et al.'s (2022) earthquake adjustment study used SEM to examine the directional effect with correlations and found that including additional variables in the PMT highlighted in the literature increases the explanatory power by 3.3% to 9.9% compared to the original PMT model.

Building off Huntsman et al.'s (2021) study examining tornado adjustment behavior among college students, we also explore grouping adjustment measures. Huntsman et al. (2021) grouped hazard adjustments into basic adjustments and complex adjustments[1], arguing that drivers of adoption intentions vary depending on the complexity of the activity. The authors found that risk perceptions were more important in complex adjustment models, suggesting that deciding to adopt a complex activity (e.g., installing a storm shelter) requires more emotional motivation, as compared to basic activities, which are easier to justify given their low cost and broad applicability (Huntsman et al. 2021). Huntsman et al. (2021), however, relied on a student sample, coming with all the inherent limitations of a student sample. Thus, this study will combine the two approaches to test additional variables beyond the basic PMT and study Oklahoma households' tornado hazard adjustment behaviors. The research questions and hypothesized models are as follows.

RQ1: How do qualitative characteristics, hazard salience, experiences of property damage, and demographics shape households' threat appraisals towards tornado hazards in Oklahoma?

RQ2: How do PMT components (threat appraisals and coping appraisals) and demographics variables explain the variances in households' intentions in adopting each hazard adjustment?

[1] Basic and complex adjustments intentions are defined in section 4(d).

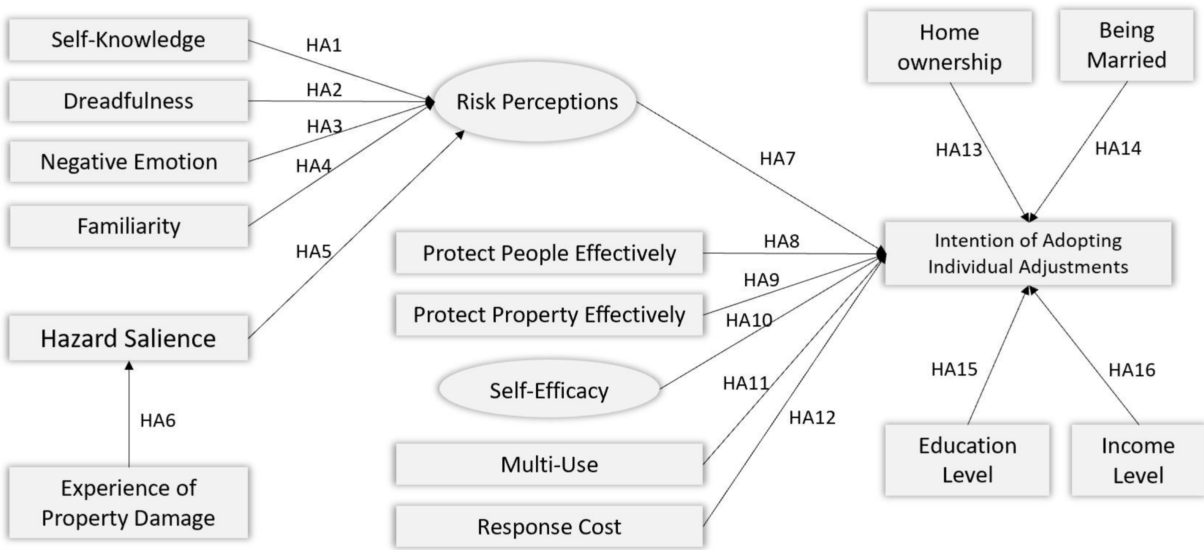

Figure 2: Hypothesized Individual Model[2]

RQ3: How do PMT components (threat appraisals and coping appraisals) and demographics variables explain the variances in households' intentions in adopting basic adjustments?

RQ4: How do PMT components (threat appraisals and coping appraisals) and demographics variables explain the variances in households' intentions in adopting complex adjustments?

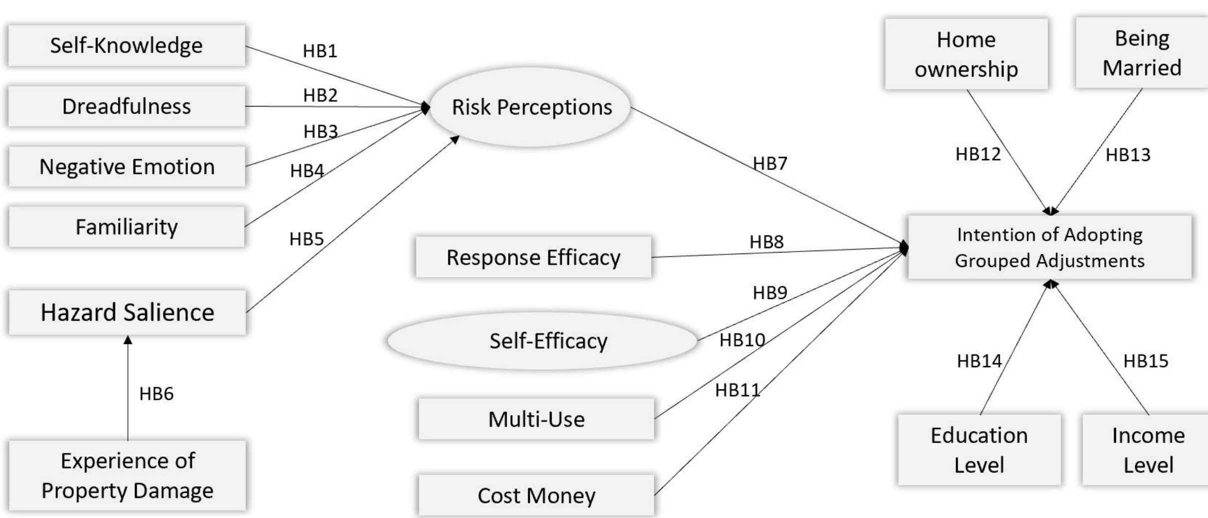

Figure 3: Hypothesized Grouped Model

[2] Observed variables in squares and latent variables in circles.

3. Methods

a. Data Collection

This study targets households from 27 counties in Oklahoma that frequently experience tornado threats (Figure 4). Since some studies suggested race affects the adoption of adjustment (Finucane et al. 2000), we oversampled non-white household groups. A disproportionate procedure was used to select 480 household addresses from each African American, Asian, Hispanic, Native American, and White households within the 27 counties. The questionnaires were sent by *Oklahoma Direct* from August to November of 2019. Following Dillman et al. (2014), we sent each household as many as three survey packages (waves 1, 3, and 4) and one reminder postcard (wave 2). One of these packages includes a pre-incentive (5-dollar Amazon gift codes). The mailing list was randomly selected using the framed population above from household addresses provided by *Experian Information Solutions Inc* and then used to match with the mailing address data provided by *Oklahoma Direct,* a survey company. We removed 129 household addresses from the original mailing list from these randomly selected households since they had moved to other areas. The questionnaires were administered by *Oklahoma Direct* from August to November of 2019. The final response rate was 17.86%, with 866 complete surveys returned, 44 rejected, and 2179 undeliverable. Our response rate is comparable to other household disaster preparedness studies (10% to 19.7%) (Mason, et al. 2018; Stock et al. 2021; Tracy, Javernick-Will, and Torres-Machi 2021). In addition, household survey studies with a less than 10% response rate have been noted as a trend in in recent years (Leeper 2019).

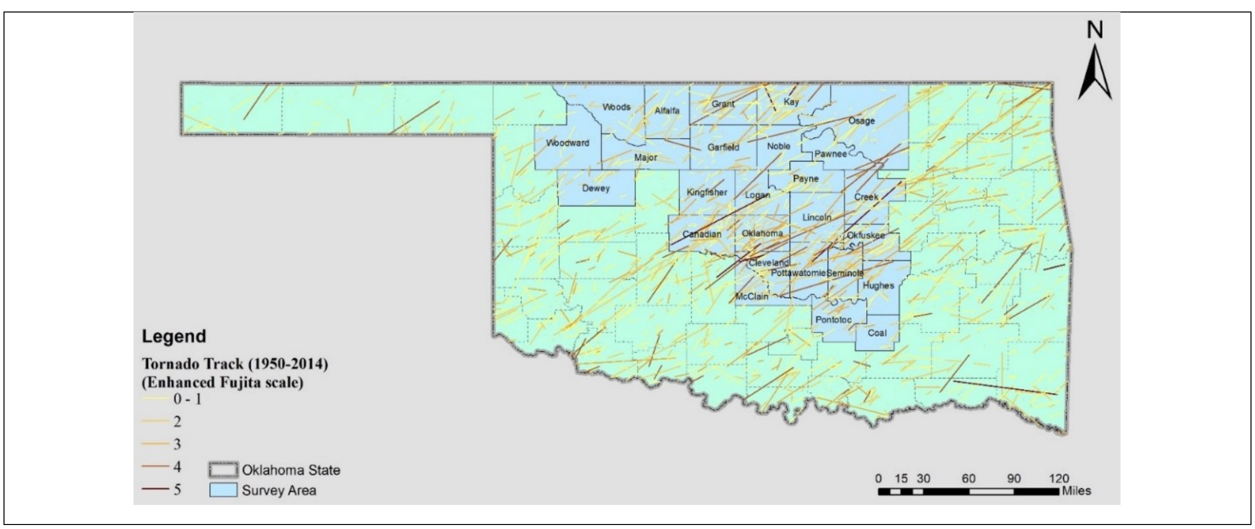

Figure 4: Survey Areas and Tornado Tracks in Oklahoma

b. Measures

This survey included 49 questions that mostly followed survey questions used in prior studies that were conducted in California, Washington, and Oklahoma (Lindell and Prater 2000; H. -C. Wu et al. 2017; and Whitney 2000; Murphy et al. 2018). In addition to previous efforts of expanding PMT, we added affective questions to our instrument to understand their impact on both risk perceptions and adjustment intentions. Our survey asked participants to report the tornado hazard salience (*How often do you think about tornadoes*) *(1=Never to 5=Daily)*; experience of property damage due to tornadoes (*In the last few years has your property had damage from a local tornado*) (*1=No damage to 5=Total collapse of home)*; and their tornado risk perceptions regarding potential damage to their homes or properties, injuries, job disruptions, and daily activity disruptions *(1=not at all likely to 5=Almost certain)* (Lindell et al. 2016; H. -C. Wu et al. 2012, 2013; H. -C. Wu et al. 2017). Participants were then asked to report their self-knowledge about tornadoes *(1=Not at all to 5=Very great extent)*, beliefs of scientists' knowledge about tornadoes *(1=Known precisely to 5=Not known)*, dreadfulness towards tornadoes *(1=Common to 5=Dread*), and negative emotion of tornadoes *(1=No negative emotion to 5=High negative emotion)*. After that, participants were asked to report: (1) the likelihood that they will adopt these hazard adjustment activities (*1=Not at all to 5=Very great extent*) and (2) the perceived attributes response efficacy (protecting person and protecting property), self-efficacy (required special knowledge, cooperation, and effort) and response costs (monetary expense and multi-use) of the 12 adjustment activities *(1=Not at all to 5=Very great extent)*. The response cost appraisal of multi-use is reversed so that the more usefulness for other hazards of an adjustment activity leads to a lower cost score of this item.

After those items, participants were also asked to provide demographic information, including age (year), gender (*Female=1, Male=0)*, race (White, African American, Native American, Asian, Hispanic), marital status *(Married=1, Unmarried = 0)*, education level *(Less than high school=1, High school graduate=2, Some college/vocational school=3, College graduate=4, Graduate school=5)*, household annual income level *(Less than \$30K=1, \$30K-\$54,999=2, \$55K-\$79,999=3, \$80K-\$104,999=4, \$105K-\$129,999=5, More than \$130K=6)*, homeownership (*Own=1, Rent=0*), and the duration of time living in their current home, duration of living in the state of Oklahoma, and family composition in terms of age groups (*How many* *members of your family including yourself are: under 18 years old, 18-65 years old, over 65 years old*) (Lindell et al. 2016; H. -C. Wu et al. 2017; H. -C. Wu et al. 2012, 2013).

c. Analyses

We first conducted correlation analyses by *Spearman Correlation* to examine the correlation among risk perceptions of tornadoes, attitudes, hazard salience, experiences, demographics characteristics, and adjustment intentions, and the correlation between coping appraisals and adjustment intentions. After that, we applied the additional factors suggested by Li et al. (2022) to the original PMT model using SEM. SEM is a statistical method that combines confirmatory factor analysis and path analysis (Weston and Gore 2006) to examine hypothesized causal relationships (Bryne 2010). Variables may be added to or dropped to better fit data. Next, following Huntsman et al. (2021) approach, Exploratory Factor Analyses (EFA) were performed to identify potential categories of those adjustment activities based on their complexity. SEM analyses were also conducted for each category identified by the factor analyses.

To build SEM models, we used AMOS 28 software and the full information maximum likelihood (FIML) estimation. FIML method enabled us to preserve the full number of records, in comparison to listwise deletion, which tends to eliminate all the records with missing values (Enders and Bandalos 2001). To measure how well the model represents the observed data, frequently used fit indexes such as the comparative fit index (CFI), the normed fit index (NFI), and the root-mean-square error of approximation (RMSEA) (Bentler 1990a, 1990b; Bryne 2010) were applied in our study. A model is considered acceptable if the CFI reaches a minimum threshold of .90 (Hu and Bentler 1999; Marsh and Hocevar 1985), the RMSEA is below .08 (Browne and Cudeck 1992), and the Chi2/df ratio should not exceed the range of 2–5 (Marsh and Hocevar 1985). Assumptions for SEM models are tested through SPSS AMOS. We apply bootstrapping methods to mitigate multivariate normality concerns in our SEM models (Hancock and Liu 2012), and control for Type I errors given the multiple variables incorporated in each SEM model (Rasmussen 1988; Keselman et al. 2008). We performed bias-corrected percentile bootstrapping at a 95% confidence interval with 2000 bootstrap samples (Tang and Feng 2018). To further control for Type I errors in our models, we apply Benjamini-Hochberg correction, as the Benjamini-Hochberg correction is appropriate for SEM analyses and less conservative than the Bonferroni methods (Cribbie 2007). To apply for Benjamini-Hochberg correction, we set the false discovery rate as 0.05, which is conventionally used (Thissen, Steinberg, and Kuang 2002).

Modification Indices were also used in the SEM analyses to identify statistically significant covariances that would improve the model's fit to the data (Lei and Wu 2007).

4. Results

a. Descriptive statistics

The descriptive statistics are reported in Appendix Table C1 and C2. Overall, the intentions of adopting each of the 12 hazard adjustments are at a moderate to a high level (*Min = 3.61, Max = 4.75*). As for hazard salience, the study participants tend to think of tornadoes between once a month and once a year (*M=2.51, SD=0.79*). Oklahomans generally have little experience with property damage from tornadoes (*M=1.33, SD=0.72*). In regard to risk perceptions, our study participants believe that tornadoes have a little chance to damage their homes (*M=2.63, SD=1.03*), injure their family members (*M=2.17, SD=1.05*), disrupt their job activities (*M=2.25, SD=1.15*), and disrupt their daily routines (*M=2.56, SD=1.16*) and a moderate chance to cause damages to their city (*M=3.25, SD=1.18*).

Study participants have high intentions of adopting adjustments, especially for basic adjustments (M=4.11, SD=0.81). For both groups of adjustments, participants' perceived response efficacy is slightly higher than the moderate level, while their perceived self-efficacy is slightly lower than the moderate level. The participants believe both basic (M=1.79, SD=0.83) and complex (tornado-specific) (M=2.54, SD=0.88) adjustments are useful for hazards other than tornadoes, but the usefulness for other hazards is higher for basic adjustments. The response cost of complex (tornado-specific) adjustments (M=2.94, SD=0.70) is believed to be higher than basic adjustments (M=2.10, SD=0.81).

The average age of respondents is 55.2 years old and respondents have lived in Oklahoma for 38.4 years on average. In our sample, 50.3% of them are female, 65.1% identify as White, 82.4% are homeowners, and 64.5% are married. Most of these participants have attended at least some college, and their income evenly spreads among each category. Overall, the households in our sample are older, better educated, with more house owners and married persons in comparison to census data of Oklahoma in 2019 (United States Census Bureau 2019) (See Table 1). Due to our race disproportionate procedure, we have obtained more Native American and Asian households in our sample.

Table 1: Demographics Variable Difference (Household Survey vs. 2019 Census)

	Survey	Census
Age	55.2	36.6
Bachelor's degree or higher	57.4%	25.5%
Median household income*	55K-80K	73k
Homeownership	82.4%	57.5%
Female	50.3%	50.4%
Married	64.5%	49.3%
White	65.1%	72.3%
African American	4.7%	7.3%
Native American	11.0%	7.6%
Asian	9.6%	2.2%
Hispanic	8.7%	10.6%

*Household income data were collected using a categorical variable in the survey

b. Correlation Analyses

According to the correlation analyses, we found that all the tornado risk perception items are significantly and positively correlated with dreadfulness (*r range from .15** to .25***) and negative emotion (*r range from .22** to .29***), while self-knowledge is only correlated with the risk perceptions of city damage (*r = .14***)[3]. Tornado hazard salience (*r range from .11** to .23**)* and experiences of property damage (*r range from .10** to .26**)* are both significantly correlated with all the risk perception items, while these two variables are also correlated with each other (*r = .12***). Risk perceptions are significantly correlated with households' intentions of signing up for smartphone alert (*r range from .09* to .15***), installing a storm shelter (*r range from .10** to .20***), developing an emergency plan (*r range from .08* to .13***), attending first-aid training (*r range from .10** to .15***), storing a three-day supply of food (*r range from .10** to .14***), and storing a three-day supply of water (*r range from .10** to .15***), while for other adjustment activities, risk perceptions have little to no correlation.

In terms of demographic characteristics, White ethnicity is negatively correlated with all risk perception items (*r range from -.08* to -.14***) except for city damage risk, while other races have little to no correlation with risk perceptions. Being married and being homeowners are significantly and strongly correlated with adjustment intentions directly. For example, being homeowners is strongly correlated with households' intentions of purchasing home insurance (*r = .43***) and installing a storm shelter (*r = .24***); being married is strongly correlated with the

[3] ** means the test statistic is significant at .01 level; * means the test statistic is significant at .05 level

households' intention of installing storm shelter ($r = .24^{**}$). The education level and income level also matter in some cases of adopting adjustment activities, such as the strong correlation of income level with installing storm shelters ($r = .28^{*}$) and purchasing home insurance ($r = .36^{*}$). Other demographics like age, being female, tenure, and house composition variables are not significantly correlated with risk perceptions or adjustment intentions much.

With respect to coping appraisals of response efficacy, protecting person effectively is significantly correlated with each of the adjustment intentions, especially for intentions of signing up for smartphone alerts ($r = .41^{**}$), developing an emergency plan ($r = .39^{**}$), storing a three-day supply of food ($r = .38^{**}$), and storing a three-day supply of water ($r = .41^{**}$). Protecting property effectively is also correlated with most of the adjustment intentions, but their correlations are not as strong as protecting persons effectively (*r range from .10** (installing a storm shelter) to .25** (shutting off utility)*). For self-efficacy, we found requiring special knowledge is negatively correlated with households' intentions of having a flashlight ($r = -.23^{**}$) but positively correlated with the intention of attending the first-aid training ($r = .13^{**}$); requiring effort is negatively correlated with intentions of signing up for smartphone alert ($r = -.22^{**}$) and installing a storm shelter ($r = -.13^{**}$); requiring cooperation is negatively correlated with intentions of signing up for smart phone alert ($r = -.18^{**}$), shutting off utility ($r = -.16^{**}$), having a flashlight ($r = -.22^{**}$), but positively correlated with developing an emergency plan ($r = .38^{**}$). The last construct of coping appraisals is response cost, and we found that lack of usefulness for other hazards has an overall strong and negative correlation with all the adjustment intentions (*r range from -.11** (installing storm shelter) to -.40** (storing three-day supply of food)*), while costing money is only negatively correlated with households' intentions of signing up for smartphone alert ($r = -.32^{**}$), installing storm shelter ($r = -.13^{**}$), and shutting off utilities ($r = -.19^{**}$).

c. Individual SEM Analyses

We first ran SEM analyses for original PMT components, where we treat risk perceptions as the only threat appraisal component; protecting people effectively and protecting property effectively as coping appraisal components that represent response efficacy; requiring special knowledge, requiring efforts, and requiring cooperation as coping appraisal components that represent self-efficacy; and costing money as the only coping appraisal component that represents response cost. The original PMT model explains 3.9% (having a flashlight) to 31.6% (signing up for smartphone alert) variances.

To answer the first two research questions (RQ1 and RQ2), we ran SEM analysis for each individual adjustment activity by adding additional variables suggested by Li, et al. (2022). We also added factors that show significance in correlation analyses and eliminated paths from the base model that did not show significance in our data. The SEM analyses for each adjustment activity are reported in Table 2, 3 and Figure A1-12, all the individual models pass the threshold of model fit indexes. The quality of all the individual SEM models is reflected both in the good overall model fit indexes and in the individual factor loadings (Cronbach's Alpha >.80; Factor Loadings > .50). The measurement model shows strong model-fit statistics with RMSEA (.042-.050) and CFI (.931-.954) meeting preferred levels (Bentler 1990a, 1990b; Bryne 2010). The new structural models after adding the additional drivers of adjustment intentions and risk perceptions explain 13.1% (having a first-aid kit) to 37.3% (signing up for smartphone alert) of total variances across all the individual adjustment models. The new models explain 1.8% (having a weather radio) to 19.5% (purchasing homeowner insurance) more variances than the original PMT models. As suggested by Babcicky & Seebauer (2019), we only deem the effect size that is above 0.10 as reportable. Self-knowledge, negative emotion, and dreadfulness are positive and significant predictors of risk perceptions across all the individual adjustment models, while the effect sizes of dreadfulness and negative emotion are slightly larger than self-knowledge. Disaster experience has a positive effect on hazard salience, while hazard salience, in turn, has a positive relationship with risk perceptions for all adjustments. We also found that White ethnicity has a negative effect on households' risk perceptions for all adjustments, indicating that White respondents perceive less risk of tornadoes than other race groups.

Based on our findings (Table 2), risk perceptions significantly and positively predict households' intentions of installing storm shelter (*B = .16***) and attending the first-aid training (*B = .11***). With respect to response efficacy, protecting persons effectively has a significant and positive effect on adjustment intentions across all the adjustment activities except for purchasing homeowner insurance, shutting off utilities, and having a fire extinguisher, while protecting property effectively does not show much significance in predicting adjustment intentions. Requiring special knowledge, efforts, and cooperation result in a significant and negative impact on intentions of installing storm shelter (*B = -.11***), shutting off utilities (*B = -.19***), developing an emergency plan (*B = -.15***), and having a flashlight (*B = -.18***). In terms of response cost appraisals, lack of usefulness for other hazards plays an important role in predicting adjustment intentions across all the adjustment activities, its negative effect is especially strong in predicting storing a three-day supply of food (B = -.*33***) and storing a three-day supply of water intentions (B = -.*28***). Costing money is another aspect of the response cost appraisal, it has a negative effect on adjustment intentions, and the effects are significant in models of signing up for smartphone alerts (B = -.*23***), installing storm shelter (B = -.*12***), having a weather radio (B = -.*22***), and storing a three-day supply of food (B = -.*11***).

Focusing on noticeable effects of demographic characteristics here, being homeowners make households more likely to install storm shelter (B = .*13***), purchase home insurance (B = .*31***), and shut off utilities (B = .*15***). Being married stimulates households' intentions of signing up for smartphone alert (B = .*10***), installing storm shelter (B = .*13***), and shutting off utilities (B = .*15***). The education level of households only matters in their intention of attending the first-aid training (B = .*11***), the education effect is either weak or not significant in other cases. Households with a higher income are more likely to install storm shelter (B = .*15***) and purchase home insurance (B = .*16***).

Table 2: Modified Conceptual Model for Individual Adjustments

	Standardized Regression paths	Individual Tornado Hazard Adjustment Intentions											
		Smart-phone Alert	Storm Shelter	Home-owner Insurance	Weather Radio	Shut off Utility	Emergency Plan	Flashlight	Fire Extinguisher	First-aid Kit	First-aid Training	Three-day Food	Three-day Water
QC†	Self-knowledge –> risk perception (HA1)	.11**^{B}	.12**^{B}	.11**^{B}	.11**^{B}	.12**^{B}	.11*^{B}	.11**^{B}	.79**^{B}	.12**^{B}	.11**^{B}	.12**^{B}	.11**^{B}
	Dreadfulness –> risk perception (HA2)	.15**^{B}	.15**^{B}	.15**^{B}	.15**^{B}	.16**^{B}	.17**^{B}	.15**^{B}	.15**^{B}	.15**^{B}	.15**^{B}	.15**^{B}	.15**^{B}
	Negative emotion –> risk perception (HA3)	.21**^{B}	.21**^{B}	.20**^{B}	.21**^{B}	.21**^{B}	.23**^{B}	.21**^{B}	.22**^{B}	.21**^{B}	.20**^{B}	.21**^{B}	.21**^{B}
DC†	White –> risk perception	-.11**^{B}	-.11**^{B}	-.10**^{B}	-.11**^{B}	-.11**^{B}	-.11**^{B}	-.11**^{B}	-.22**^{B}	-.10**^{B}	-.11**^{B}	-.11**^{B}	-.11**^{B}
Hazard salience –> Risk perception (HA5)		.13**^{B}	.13**^{B}	.14**^{B}	.13**^{B}	.14**^{B}	.13**^{B}	.13**^{B}	.13**^{B}	.13**^{B}	.13**^{B}	.14**^{B}	.13**^{B}
TA†	Risk perception –> adjustment intention (HA7)	.08**^{B}	.16**^{B}	.03	.06	-.02	.05	.01	.08*^{B}	.04	.11**^{B}	.07*^{B}	.09**^{B}
Experience of property damage –> hazard salience (HA6)		.10**^{B}	.09**^{B}	.13**^{B}	.09**^{B}	.11**^{B}	.12**^{B}	.12**^{B}	.09**^{B}	.12**^{B}	.09**^{B}	.13**^{B}	.09**^{B}
CA†	Response efficacy (protect person effectively) –> adjustment intention (HA8)	.38**^{B}	.28**^{B}	.04	.31**^{B}	.03	.26**^{B}	.11*^{B}	.09	.15**^{B}	.20**^{B}	.25**^{B}	.25**^{B}
	Response efficacy (protect property effectively) –> adjustment intention (HA9)	-.04	.12**^{B}	.09*^{B}	.00	.20**^{B}	.14**^{B}	-.04	.10	-.01	.03	.10**^{B}	.11**^{B}
	Self-efficacy –> adjustment intention (HA10)	-.07	-.11**^{B}	-.07*	.11*^{B}	-.19**^{B}	-.15**^{B}	-.18*^{B}	-.04	-.06	-.05	-.07	-.07
	Response cost (multi-use) –> adjustment intention (HA11)	-.26**^{B}	-.12**^{B}	-.20**^{B}	-.16**^{B}	-.28**^{B}	-.28**^{B}	-.29**^{B}	-.19**^{B}	-.24**^{B}	-.21**^{B}	-.33**^{B}	-.28**^{B}
	Response cost (cost money) –>adjustment intention(HA12)	-.23**^{B}	-.12**^{B}	.03	-.22**^{B}	-.02	-.02	.08	-.09	-.01	-.08	-.11*^{B}	-.06
DC†	Home ownership –> adjustment intention (HA13)	.05	.13**^{B}	.31**^{B}	.07*^{B}	.15**^{B}	.05	.09*^{B}	.08*^{B}	.08*^{B}	.03	.09**^{B}	.06
	Married status –> adjustment intention (HA14)	.10**^{B}	.13**^{B}	.01	.06	.17**^{B}	.08**^{B}	.04	.08*^{B}	.08*^{B}	.01	-.02	-.05
	Education level –> adjustment intention (HA15)	.04	.04	.08**^{B}	.04	.07^{B}	-.03	.01	.01	.01	.11**^{B}	.01	.01
	Income level –> adjustment intention (HA16)	-.03	.15**^{B}	.16**^{B}	.03	-.08*^{B}	.02	.04	-.02	.00	-.09*^{B}	-.04	.01
Model Fit Indexes		Smart-phone Alert	Storm Shelter	Home-owner Insurance	Weather Radio	Shut off Utility	Emergency Plan	Flashlight	Fire Extinguisher	First-aid Kit	First-aid Training	Three-day Food	Three-day Water
χ^2 (df)		578.4 (195)	537.8 (188)	578.7 (200)	508.6 (194)	619.4 (197)	475.2 (190)	568.1 (202)	620.0 (202)	584.9 (201)	536.1 (193)	512.3 (188)	499.8 (193)
χ^2/df		2.966	2.861	2.893	2.622	3.144	2.501	2.812	3.069	2.910	2.778	2.725	2.590
CFI		.939	.935	.931	.951	.933	.950	.951	.937	.936	.937	.947	.954
NFI		.912	.904	.900	.924	.906	.920	.926	.910	.906	.905	.920	.928
RMSEA		.048	.046	.047	.043	.050	.042	.046	.049	.047	.045	.045	.043
10%-CI RMSEA		.043-.052	.042-.051	.042-.051	.039-.048	.045-.054	.037-.046	.041-.050	.045-.053	.043-.051	.041-.050	.040-.049	.038-.048
SMC for the adjustment intention		.373	.260	.239	.202	.231	.261	.133	.132	.131	.142	.260	.238

†TA: Threat Appraisal; CA: Coping Appraisal; QC: qualitative characteristics; DC: Demographics; SE: Self-efficacy; RP: Risk Perception
*p<.05; **p<.01; ^{B}: significance after Benjamini-Hochberg correction; standardized path coefficients and correlations; SMC = squared multiple correlation; n = 866.
All the coefficient estimates reported are standardized coefficient estimates.

Table 3: Factor Loadings for Individual Models

	Standardized Factor Loadings	Smart-phone Alert	Storm Shelter	Home-owner Insurance	Weather Radio	Shut off Utility	Emergency Plan	Flashlight	Fire Extinguisher	First-aid Kit	First-aid Training	Three-day Food	Three-day Water
SE†	Self-efficacy –> require special knowledge	.80**	.75**	.78**	.83**	.80**	.60**	.93**	.80**	.82**	.73**	.82**	.88**
	Self-efficacy –> require efforts	.92**	.87**	.91**	.92**	.91**	.90**	.96**	.95**	.93**	.90**	.87**	.86**
	Self-efficacy –> require cooperation	.79**	.77**	.78**	.87**	.76**	.81**	.90**	.76**	.73**	.66**	.79**	.88**
.RP†	Risk Perception –> perceived risk of city damage	.80**	.79**	.79**	.80**	.78**	.79**	.80**	.80**	.80**	.83**	.80**	.80**
	Risk Perception –> perceived risk of home damage	.82**	.83**	.82**	.83**	.84**	.83**	.82**	.82**	.82**	.79**	.82**	.82**
	Risk Perception –> perceived risk of family injury	.85**	.85**	.85**	.86**	.84**	.85**	.85**	.86**	.85**	.86**	.85**	.86**
	Risk Perception –> perceived risk of job activity disruption	.63**	.63**	.63**	.64**	.59**	.64**	.64**	.63**	.63**	.63**	.63**	.64**
	Risk Perception –> perceived risk of daily activity disruption	.66**	.66**	.65**	.66**	.66**	.66**	.65**	.65**	.65**	.66**	.65**	.66**

d. Exploratory Factor Analyses for basic and complex adjustments

We performed a common factor analysis (maximum likelihood option) on all the adjustment activities to assess their dimensionality; the maximum likelihood option for extraction was used. The loadings were rotated using the Promax option since the latent traits are assumed to be correlated to some extent. Like Huntsman et al. (2021), our EFA results suggest a 2-factor model for adjustment activities. All factor loadings are above the desired threshold of .40 (Hinkin 1998). Thus, we categorize the 12 adjustment activities into two groups – basic adjustments and complex (largely tornado-specific) adjustments. Based on the results of EFA, we found that basic adjustments include shutting off utilities, developing an emergency plan, having a flashlight, having a fire extinguisher, having a first-aid kit, attending first-aid training, storing three-day food, and storing three-day water. Complex adjustments include signing up for smartphone alert, installing a storm shelter, purchasing the home insurance, and having a weather radio. We obtained the average values for adjustment intentions, response efficacy, self-efficacy (require special knowledge, require effort, require cooperation), response cost (multi-use, cost money) for the basic adjustment group and complex adjustment group respectively, in order to analyze the SEM models for the two groups.

e. Grouped SEM Analyses

Based on our categorization of the adjustment activities, each category can be analyzed by applying the additional adjustment intention and risk perception drivers to the original PMT model. Overall, the two SEM models for the two adjustment groups have good model fit based on the model fit indexes. The individual factor loadings also indicate good quality of the measurement models (all *Cronbach's Alpha* > .60, except for the multi-use (.56) and costing money (.54) for the complex adjustments group; Factor Loadings > .50 (Hair et al. 2010)). The measurement model shows strong model-fit statistics with RMSEA (.047-.048) and CFI (.952-.959), meeting preferred levels. The grouped measurement models have slightly better model fit with RMSEA and CFI than the individual models. Details of our findings are reported in Table 4, 5, and Figure B1-2.

Based on our SEM analyses on each adjustment group, we found that the model we proposed in this study explains 29.4% of the total variances in the basic adjustments and 33.0% of the total variances in the complex adjustments, which are much higher than the average variances explained in each individual adjustment model. The following shows our findings for RQ3 and RQ4.

Table 4 shows that risk perceptions play an important role in predicting intentions of adopting complex adjustments ($B = .14^{**}$), while the effect size of risk perceptions is smaller for the intention of basic adjustments. Response efficacy has a significant and positive effect on households' intentions of adopting both complex ($B = .23^{**}$) and basic adjustments ($B = .20^{**}$). Requiring knowledge, efforts, and cooperation has an adverse effect on households' intentions of adopting basic adjustments ($B = -.19^{**}$), while it is less important for intentions of adopting complex adjustments. Consistent with the individual adjustment models, lack of usefulness for other hazards decreases households' intentions of adopting both basic adjustments ($B = -.42^{**}$) and complex adjustments ($B = -.31^{**}$), while costing money shows only significant and negative influence on complex adjustment intention ($B = -.10^{**}$).

Self-knowledge, dreadfulness, and negative emotions show similar patterns as we described in individual adjustment models – all three of them are significant and positive predictors of risk perceptions towards tornado hazards, while White households perceive a significantly lower level of tornado risks in both groups. Our findings on the effects of hazard salience and disaster experiences are consistent with what we found in the individual adjustment models; experience has a positive relationship with hazard salience, while hazard salience has a positive relationship with risk perceptions.

With respect to the demographic characteristics, being homeowners ($B = .19^{**}$), being married ($B = .12^{**}$), and higher income ($B = .13^{**}$) all lead to higher intentions of adopting complex adjustments, while the effect of education level is also positive but weak. Being homeowners ($B = .12^{**}$) also makes households more likely to adopt basic adjustments.

Table 4: Modified Conceptual Model for Grouped Adjustments

Standardized regression paths		Grouped Tornado Hazard Adjustment Intentions: Basic Adjustments	Grouped Tornado Hazard Adjustment Intentions: Complex (Tornado-Specific) Adjustments
QC	Self-knowledge –> risk perception (HB1)	.11**^{B}	.09*^{B}
	Dreadfulness –> risk perception (HB2)	.15**^{B}	.17**^{B}
	Negative emotion –> risk perception (HB3)	.20**^{B}	..24**^{B}
DC	White –> risk perception	-.11**^{B}	-.12**^{B}
Hazard salience –> Risk perception (HB5)		.13**^{B}	.13**^{B}
TA	Risk perception –> adjustment intention (HB7)	.08**^{B}	.14**^{B}
Experience of property damage –> hazard salience (HB6)		.12**^{B}	.13**^{B}
CA	Response efficacy –> adjustment intention (HB8)	.20**^{B}	.23**^{B}
	Self-efficacy –> adjustment intention (HB9)	-.19**^{B}	-.09*^{B}
	Response cost (multi-use) –> adjustment intention (HB10)	-.42**^{B}	-.31**^{B}
	Response cost (cost money) –> adjustment intention (HB11)	.04	-.10**^{B}
DC	Home ownership –> adjustment intention (HB12)	.12**^{B}	.19**^{B}
	Married status –> adjustment intention (HB13)	.09*^{B}	.12**^{B}
	Education level –> adjustment intention (HB14)	.06	.09*
	Income level –> adjustment intention (HB15)	-.04	.13**^{B}
Model Fit Indexes		**Basic Adjustments**	**Complex (Tornado-Specific) Adjustments**
χ^2 (df)		489.3 (169)	505.9 (168)
χ^2/df		2.896	3.011
CFI		.959	.952
NFI		.939	.930
RMSEA		.047	.048
10%-CI RMSEA		.042-.052	.043-.053
SMC for the adjustment intention		.294	.330

*p<.05; **p<.01; ^{B}: significance after Benjamini-Hochberg correction; standardized path coefficients and correlations; SMC = squared multiple correlation; n = 866.
All the coefficient estimates reported are standardized coefficient estimates.

Table 5: Factor Loadings for Grouped Models.

Standardized Factor Loadings		Basic Adjustments	Complex (Tornado-Specific) Adjustments
SE†	Self-efficacy –> require special knowledge	.92**	.88**
	Self-efficacy –> require efforts	.95**	.93**
	Self-efficacy –> require cooperation	.90**	.86**
RP†	Risk Perception –> perceived risk of city damage	.79**	.58**
	Risk Perception –> perceived risk of home damage	.82**	.81**
	Risk Perception –> perceived risk of family injury	.85**	.86**
	Risk Perception –> perceived risk of job activity disruption	.63**	.65**
	Risk Perception –> perceived risk of daily activity disruption	.65**	.68**

5. Discussion

Like previous literature, the current study has found that PMT components have significant impacts on households' intentions of adopting adjustment activities for tornado hazards. Coping appraisals appear to have a stronger predicting effect on adjustment intentions than threat appraisals, which is in line with previous work (Bubeck et al. 2012; Greer et al. 2020; Maadux and

Rogers 1983; Milne et al. 2000; H. -C. Wu et al. 2017). Consistent with Huntsman et al. (2021), we also found that threat appraisals have a stronger explanatory power in more complex adjustments, especially in the case of installing a storm shelter.

In line with prior studies, we found correlations between hazard knowledge and hazard adjustment adoption (Lindell and Whitney 2000) and between hazard knowledge and risk perceptions (Wachinger et al. 2013). In our study, self-knowledge of tornado hazards contributes as a driver of risk perceptions, which directly affect adjustment intentions. Our findings are consistent with Iorfa et al. (2020) which argues that having adequate knowledge leads to higher involvement in hazard adjustment behavior through risk perceptions. Previous studies have found that emotional responses create an affect heuristic that individuals use to quickly assess threats (Finucane et al. 2000; Huntsman et al. 2021; Keller et al. 2006) and the negative emotion is strongly associated with risk perceptions (Oh et al. 2021). This study confirms the previous findings by showing that both emotional responses of dreadfulness and negative emotions result in a higher level of risk perceptions towards tornadoes. The positive effect of experiences on salience is consistent with Wachinger et al. (2013). As for salience, we found salience is more correlated with risk perceptions rather than adjustment intentions directly, and these findings concur with previous studies (Burger and Palmer 1992; Prater and Lindell 2000). In terms of the racial and gender effects, our study finds partial evidence for the "white-male effect". We found that White respondents perceives a significant lower level of risks towards tornadoes (Finucane et al. 2000), while gender did not show much significant influence on risk perceptions in our analyses.

This study also identifies demographic characteristics that affect adjustment intentions. Consistent with previous work (Botzen and Van Den Bergh 2012; Grothmann and Reusswig 2006; Lindell and Hwang 2008; Zaalberg et al. 2009), education shows only little to no effect in both our individual adjustment models and grouped adjustment models. Consistent with Grothmann and Reusswig (2006), Harries and Penning-Rowsell (2011), and Thistlethwaite et al. (2018), we found that being a homeowner made respondents more likely to intend to adopt certain adjustments that are designed to protect their property, such as purchasing homeowner insurance and learning how to shut off utilities. While previous studies found income level has influence on adjustment intentions (Grothmann and Reusswig 2006; Stojanov et al. 2015; Thistlethwaite et al. 2018), our findings suggest income level only matters for certain adjustment activities that are costly, like installing storm shelter and purchasing homeowner insurance. In line with previous works such as

Li et al. (2022), Prater and Lindell (2000), and Russell et al. (1995), being married positively predicts hazard adjustment activities. Here, we find that marital status predicts a range of complex activities, such as signing up for smartphone alert and installing storm shelter.

Our findings lend support to the drivers of adjustment intentions and risk perceptions identified by Li et al. (2022) in the context of techna hazards. In comparison to Li et al.'s (2022) results, our models explain 13.1% to 37.3% variances, which are slightly higher than the variances explained by their SEM models (12.7% to 29.1%). The differences in the explained variances of the individual models may be due to the nature of the adjustments. For example, installing a storm shelter and purchasing home insurance require high effort and can be costly, whereas signing up for smartphone alert requires some technical literacy. While simple adjustments such as having a flashlight are usually adopted regardless of the hazard and require minimum efforts and cost, they are less likely to be explained by appraisal components and demographic factors. The results of grouped models are consistent with this conclusion – the adjustments of higher complexity are better explained by the hypothesized model (33.0%) in comparison to the basic adjustment model (29.4%). Our model also highlights the importance of demographic variables such as the relationship between race and risk perceptions and the effect of income and education on adjustment intentions. Our findings concur with Li et al.'s (2022) findings on the effect of perceived self-knowledge, emotional responses, and hazard salience on risk perception and subsequent adjustment intentions, and the effect of disaster experiences on hazard salience and, in turn, risk perception. Risk perceptions tend to be more important in hazard-specific adjustments, for both earthquakes and tornadoes. In line with Li et al.'s (2022) findings, protecting people effectively and multi-use are strong coping appraisals that affect adjustment intentions.

In addition, as mentioned previously, this study is an extension of Huntsman et al. (2021), which found that threat appraisals and coping appraisals produce differential effects depending on the type of hazard adjustment in question in a sample relying on college students. In the present study, we employ a household sample, finding the same two groups of adjustment activities: 1) basic and 2) complex. In line with Huntsman et al. (2021), our findings show that risk perceptions (threat appraisal) are a significant but weak predictor of basic adjustments and is rather a significant and stronger predictor of complex adjustments. This shows that while complex activities are determined by both coping and threat appraisals, basic adjustments are instead determined primarily by coping appraisals. This is likely because complex adjustments demand more of an emotional (fear)-based motivation to incentivize their adoption, because they are more taxing of an investment, are expensive, and are often hazard-specific (Huntsman et al. 2021).

Like the student sample in Huntsman et al. (2021), we also found response efficacy as a significant predictor of both basic and complex adjustments. In our sample, however, self-efficacy plays a more important role in households' intentions of adopting basic adjustments in comparison to complex adjustments, whereas Huntsman et al. (2021) found that self-efficacy did not significantly predict either basic or complex adjustments. Consistent with the student sample, response cost is a significant predictor of complex adjustment intentions, but not basic adjustment intentions. It also appears that response efficacy and the ability to use basic adjustments in multiple situations accounts for most of the variance in basic adjustment adoption intentions.

Our findings also show that qualitative characteristics such as self-knowledge, salience, dreadfulness, negative emotion, and experience are important across both basic and complex adjustment intentions. This in part runs contrary to Huntsman et al. (2021), where salience and experience were only significant in the complex adjustments model. These findings need future investigation to compare the drivers of hazard adjustment between college students and households. Our household sample appears to account for more variance in complex adjustment intentions with demographic variables such as marital status, education, and income. Student samples are often too homogenous along these variables to include them in models. Lastly, in our household sample, homeownership was a significant predictor of both basic and complex adjustment intentions while in Huntsman et al. (2021), homeownership only mattered for complex adjustments.

6. Conclusion

This study applies the additional drivers of adjustment intentions and risk perceptions suggested by Li et al. (2022) to examine factors that explain households' intentions of adopting basic and complex hazard adjustments in Oklahoma. Our findings demonstrate that the drivers of adjustment intentions and risk perceptions that Li et al. (2022) identified in the context of techna hazards are also relevant in natural hazards, such as tornadoes in Oklahoma, while allowing for appropriate modifications. For example, the familiarity as a driver of threat appraisals was removed due to its insignificance, education and income are added to predict the adjustment intentions, and race is found to indirectly affect adjustment intentions through threat appraisals. Building on Huntsman et al. (2021), this study provides more evidence for the potential to and utility of grouping adjustment activities in analysis. We also employ more rigorous analytical procedures, such as SEM, to better understand the numerous pathways of the PMT. Overall, these additions and classifications allow for more specificity in testing the causal pathways of the PMT, which improves our understanding of the model.

In this household study of tornado preparedness, we found perceived self-knowledge, dreadfulness, negative emotions, and hazard salience positively predict risk perceptions, while identifying as White negatively predict risk perceptions. Hazard salience is in turn affected by experience with tornadoes. While the effects of risk perception drivers are consistent across different individual adjustments and grouped adjustments, adjustment intention drivers show variances in terms of their effect sizes and significance levels. Risk perceptions are more important in complex (tornado-specific) adjustments in comparison to basic (common) adjustments. While response efficacy and multi-use are consistently significant and strong predictors of adjustment intentions, other coping appraisals (self-efficacy and response cost) only matter for certain adjustments. In terms of the demographic variables, we found homeownership and income level are strong drivers of adjustment intentions that are relatively costly (e.g., purchasing home insurance; installing a storm shelter). Likewise, married individuals are more likely to learn how to shut off their utilities, installing a storm shelter, and signing up for smartphone alert, while education level only matters in relation to attending first-aid training. The findings enrich regulators, researchers, and residents' understanding of how adjustments to tornado risks, the historically dominating hazard in the area, and adjustments to earthquake risks, the new emerging technologically triggered hazard, are shaped by various sources differently. Such insights provide scholars and emergency managers specific strategies for risk communication efforts.

As with all studies, this study has a few limitations. First, similar to other household survey studies (Jon et al. 2016; Wu, Lindell, and Prater 2012; Dow and Cutter 2000), this study included a higher portion of individuals over 65 years old, people with high education levels, and homeowners when compared to census data for the state (Table 1). Further studies should employ household survey methodologies, such as stratified sampling, that could overcome this issue. Second, self-knowledge in this study is a self-scored question, households' perceptions of their hazard-specific knowledge can deviate from their actual knowledge level. Future research should consider using objective measures of hazard knowledge and compare the results with this paper. Third, this study only uses risk perceptions to measure threat appraisals and treats emotional responses, disaster experience, and salience as risk perception drivers, while all these factors can be treated as threat appraisal components based on previous work. Future research should consider a model that threats risk perceptions, emotional responses, hazard salience and disaster experiences all as threat appraisals and examine how they interact with each other and affect adjustment intentions collectively. Fourth, based on the paths we identified in SEM analyses, there may be unrecognized mediating effects. For example, risk perceptions may mediate self-knowledge's effect on adjustment intentions. Future research should move a step forward to examine potential mediating effects among these factors. Consequently, future research should address all the mentioned limitations and provide broader perspectives on how to advance the Protection Motivation Theory to better predict the adjustment intentions.

7. Acknowledgement

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8. Data Availability Statement

All data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

9. Appendix

Appendix A: Diagrams of Individual SEM Models (With Results)

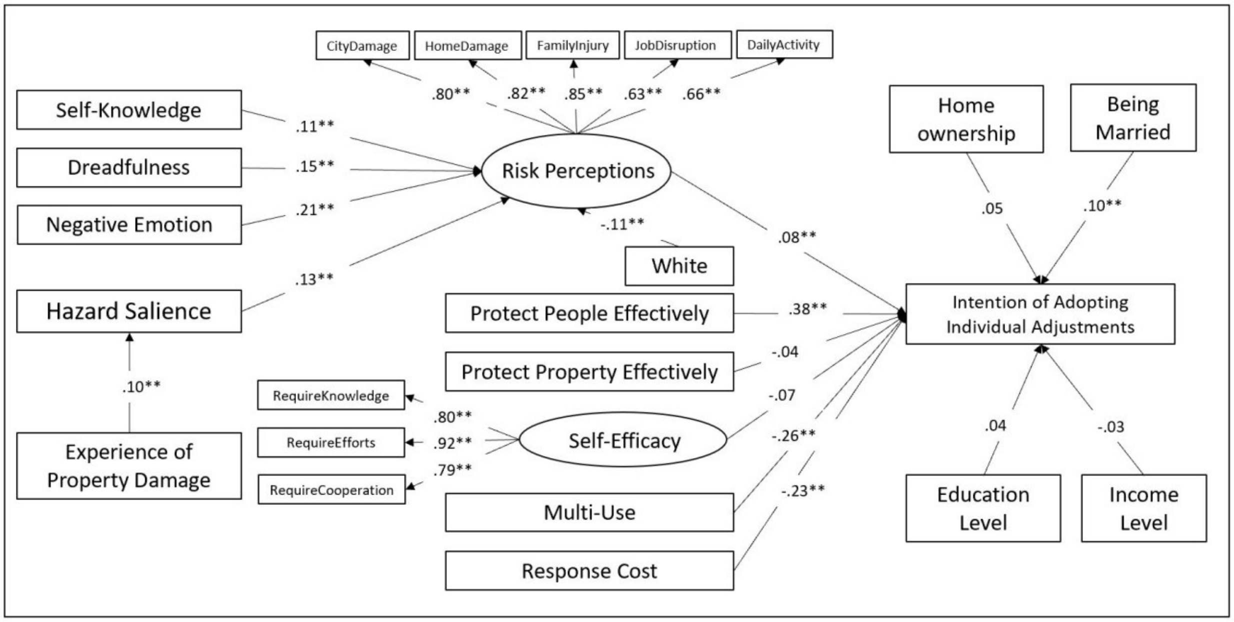

Figure A1: Individual SEM Model Results (SmartPhone)

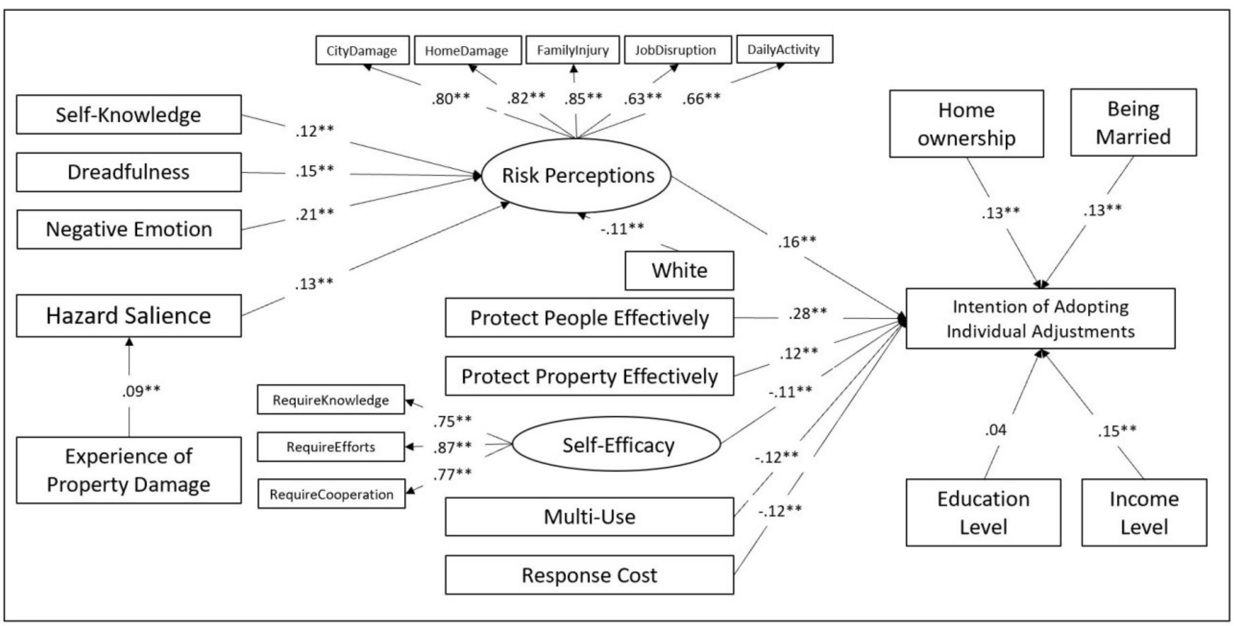

Figure A2: Individual SEM Model Results (StormShelter)

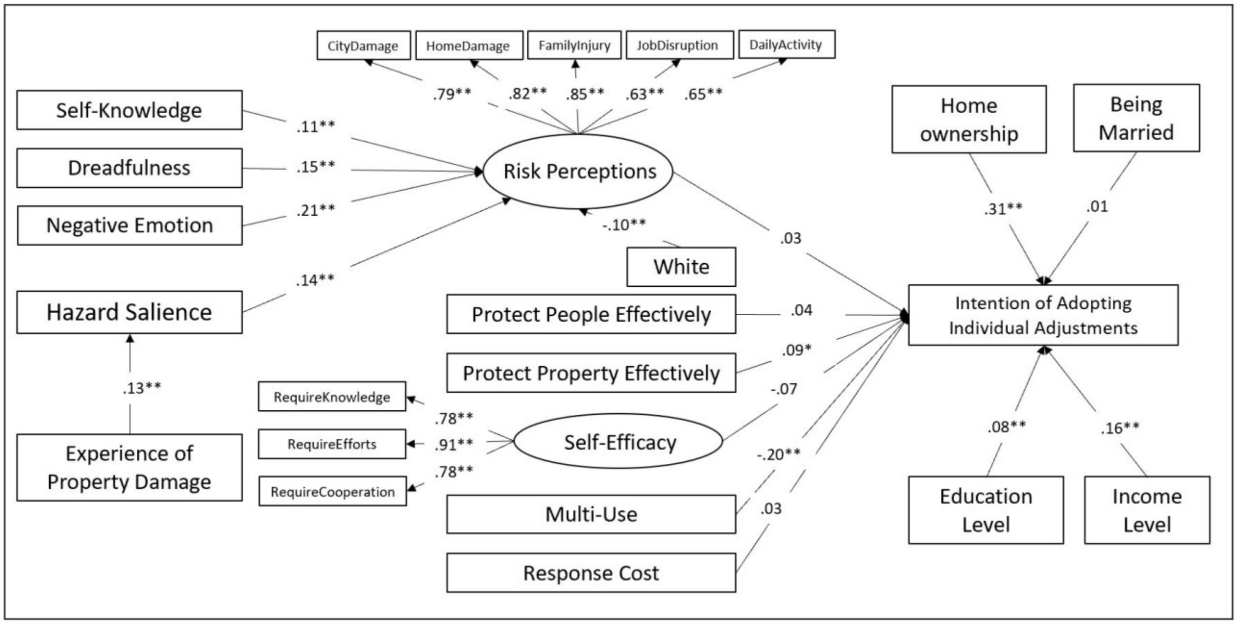

Figure A3: Individual SEM Model Results (HomeInsurance)

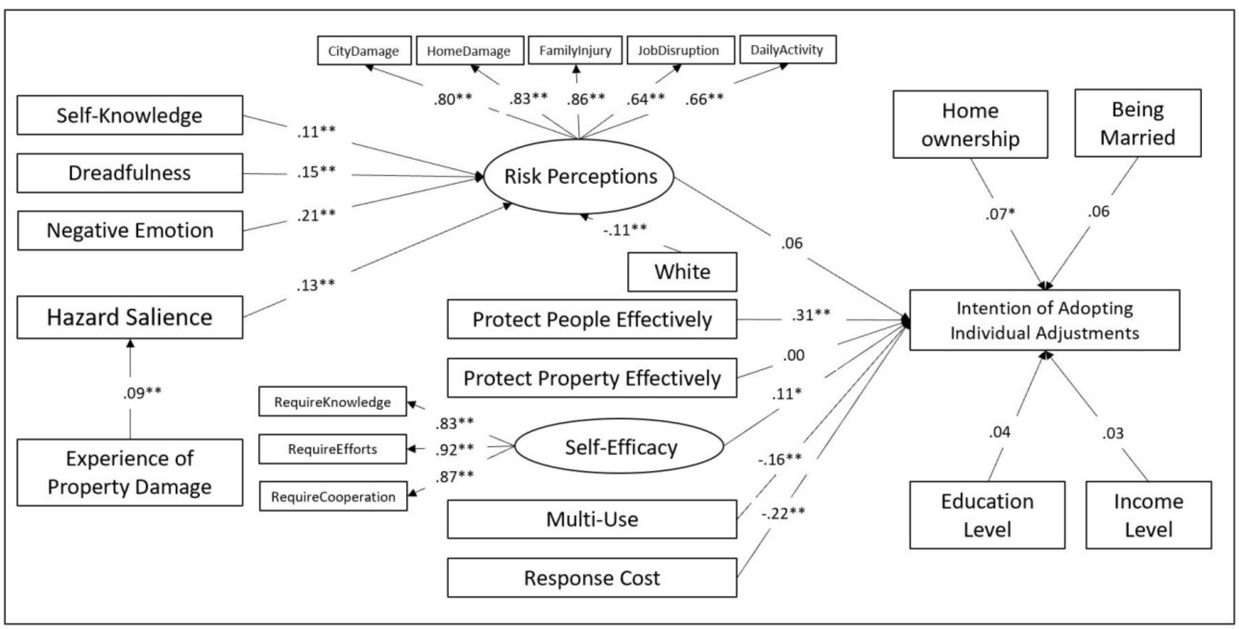

Figure A4: Individual SEM Model Results (WeatherRadio)

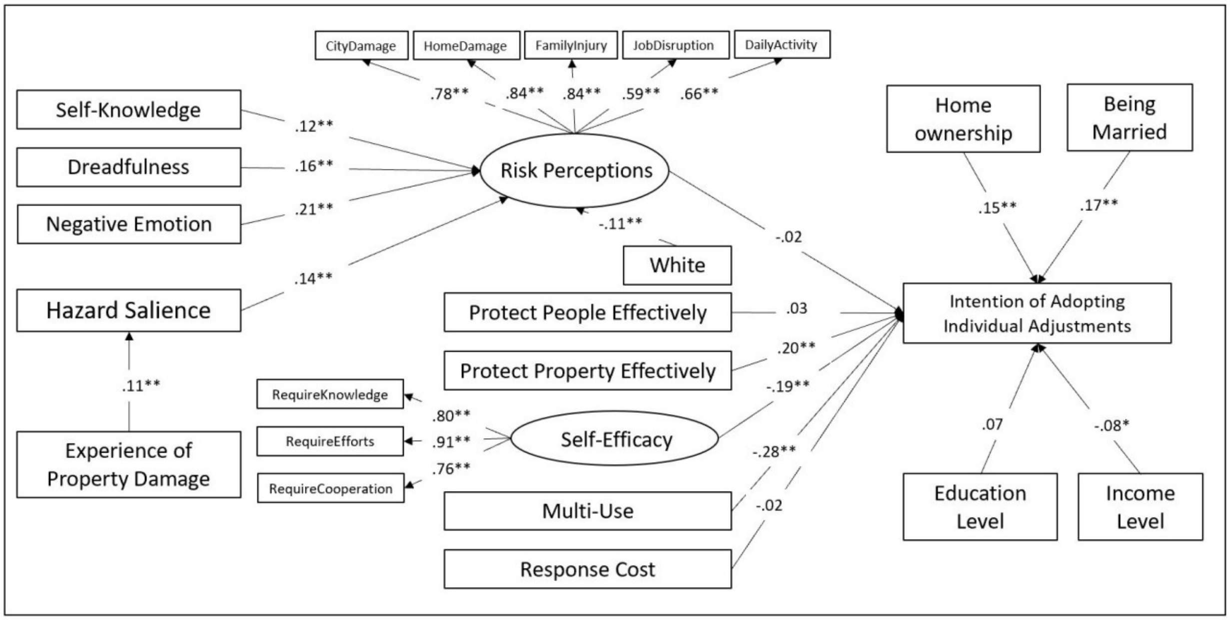

Figure A5: Individual SEM Model Results (ShutOffUtility)

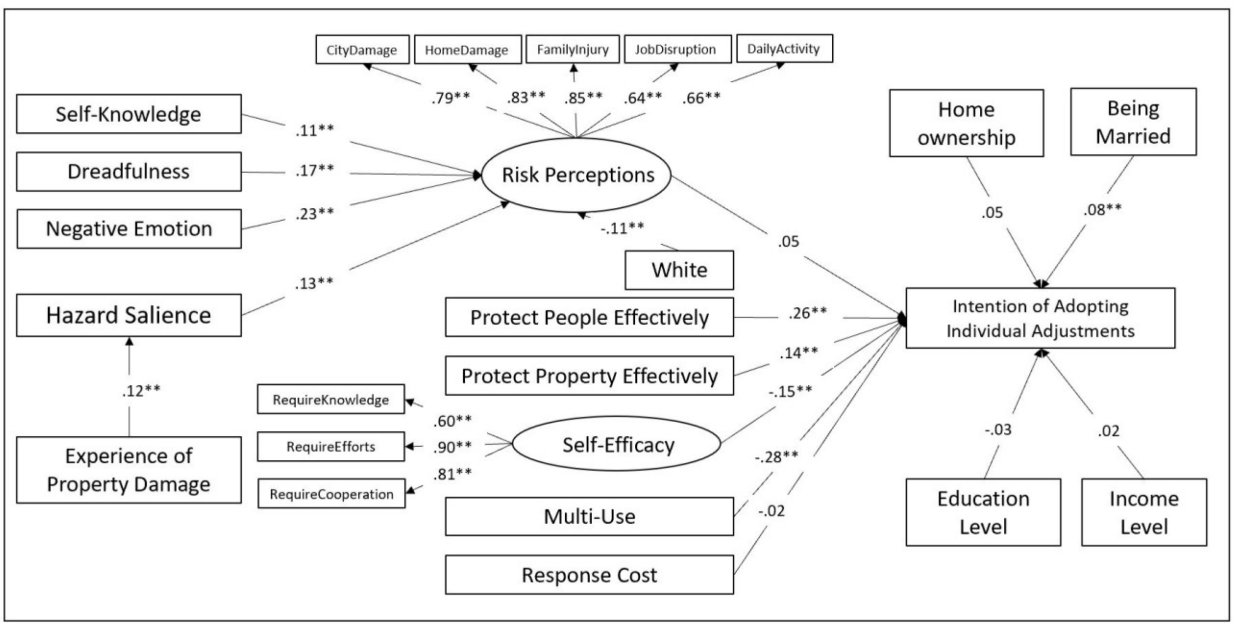

Figure A6: Individual SEM Model Results (EmergencyPlan)

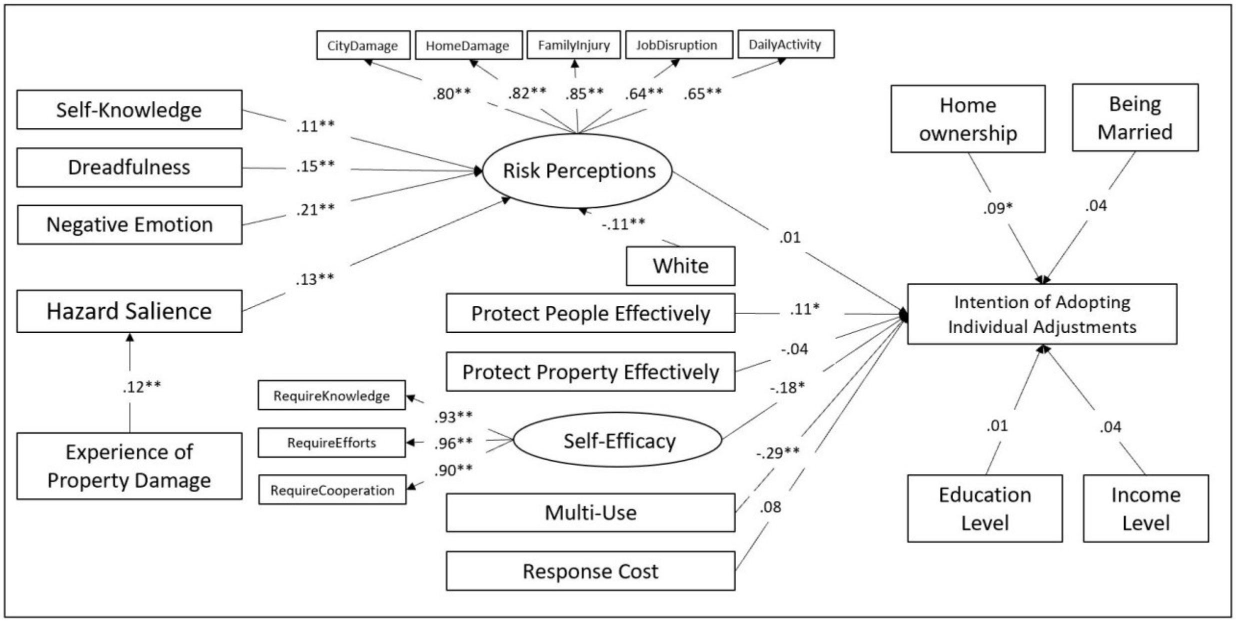

Figure A7: Individual SEM Model Results (Flashlight)

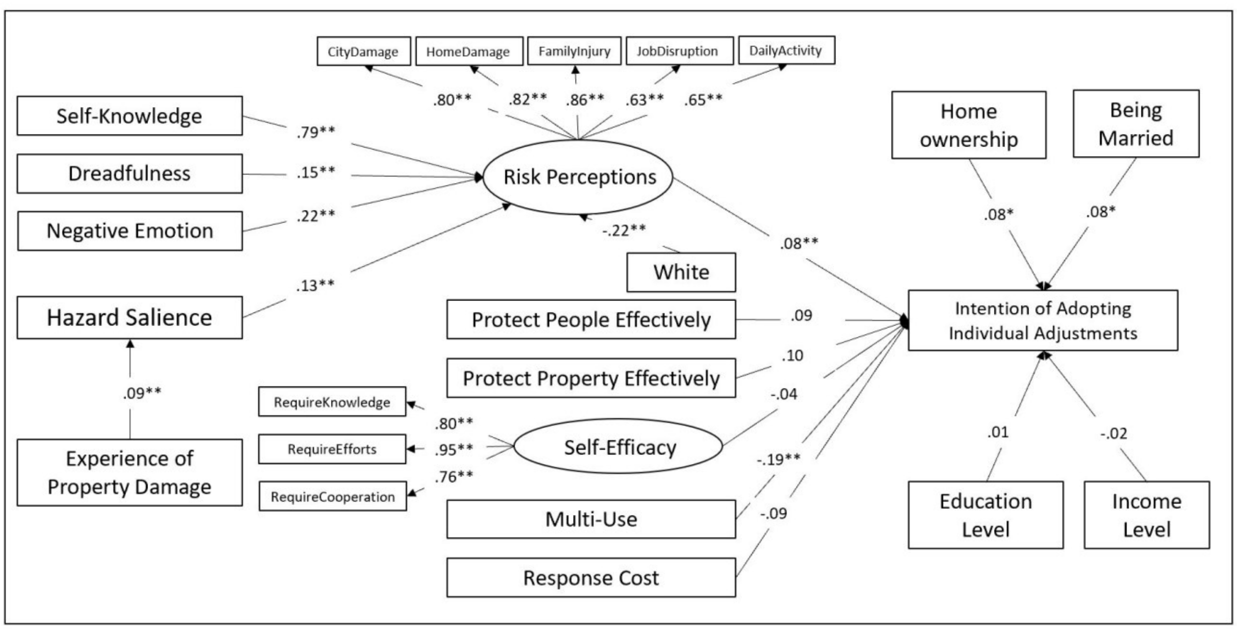

Figure A8: Individual SEM Model Results (FireExtinguisher)

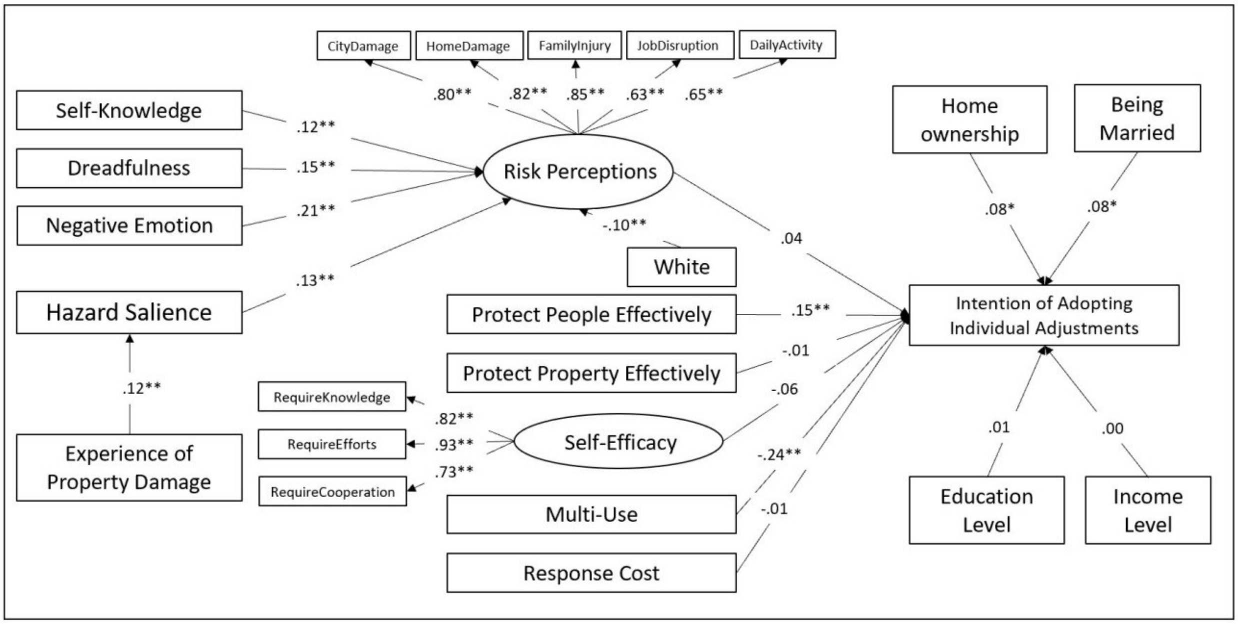

Figure A9: Individual SEM Model Results (FirstAidKit)

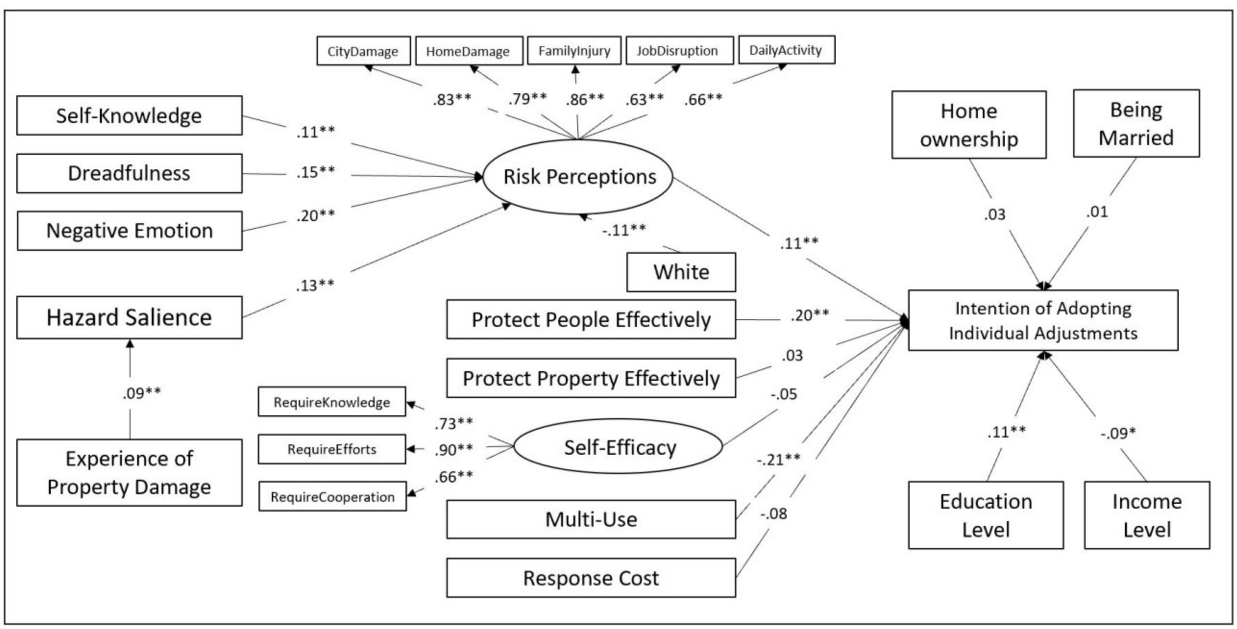

Figure A10: Individual SEM Model Results (FirstAidTraining)

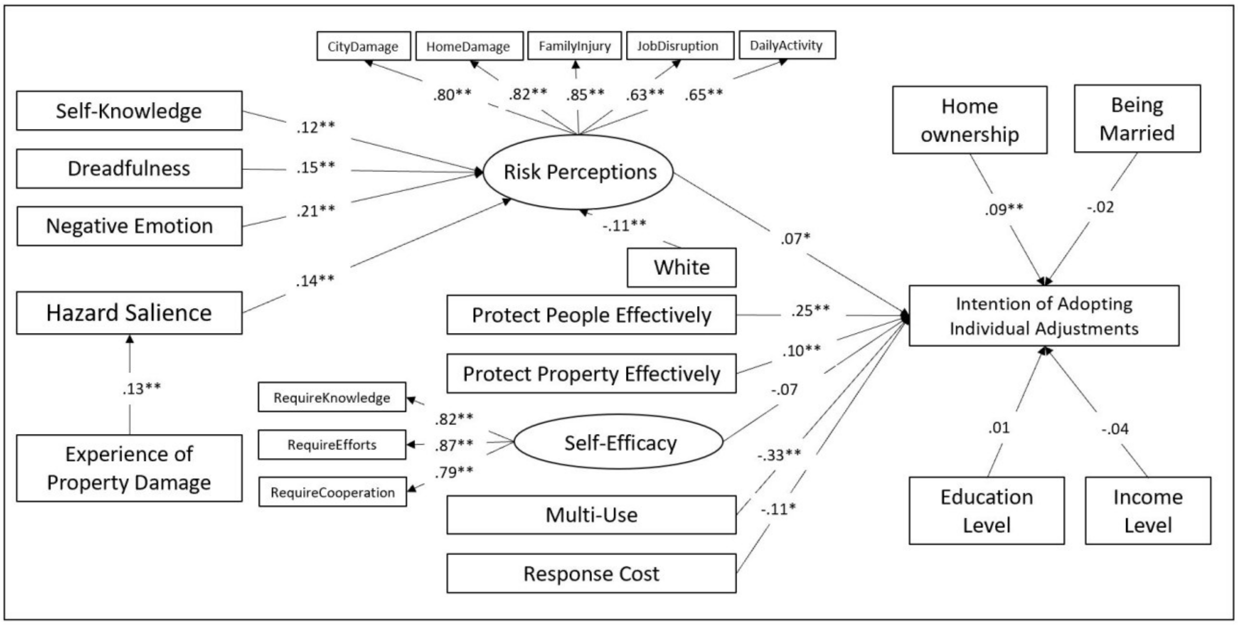

Figure A11: Individual SEM Model Results (ThreeDayFood)

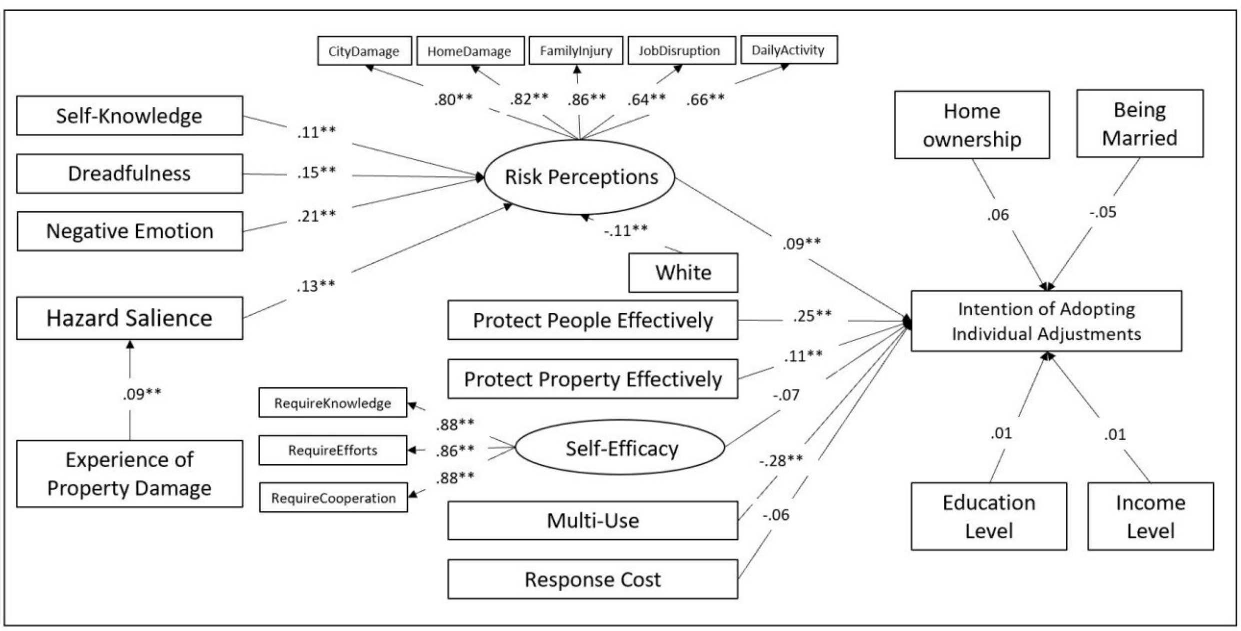

Figure A12: Individual SEM Model Results (ThreeDayWater)

Appendix B: Diagrams of Grouped SEM Models (With Results)

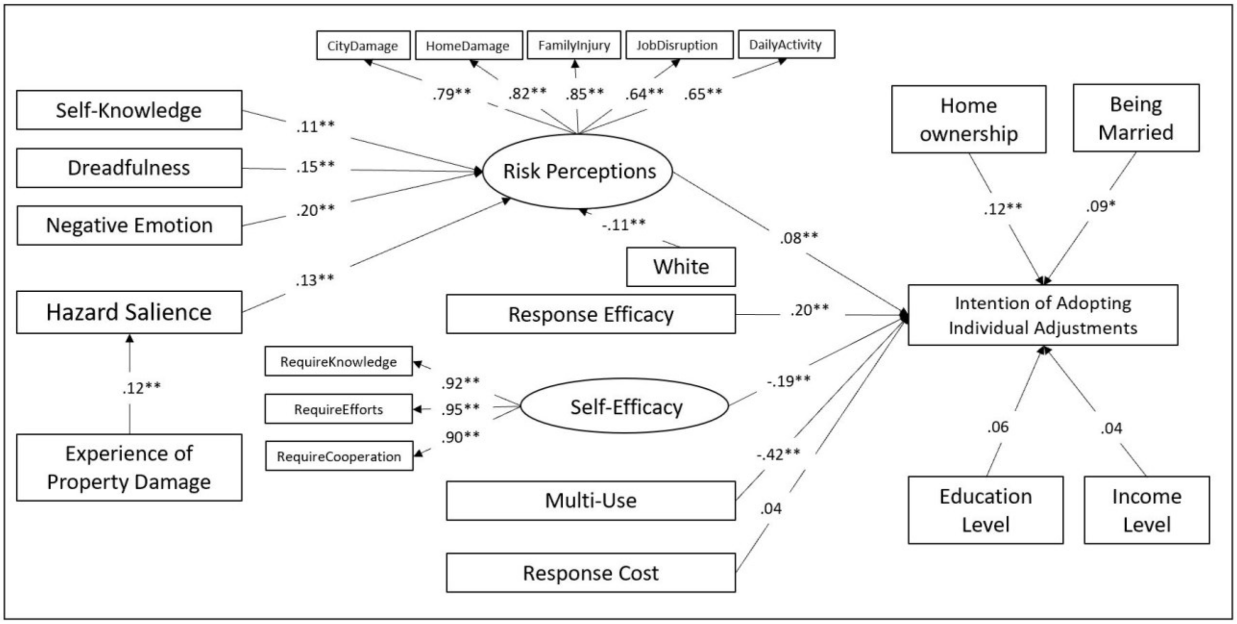

Figure B1: Grouped SEM Model Results (Basic)

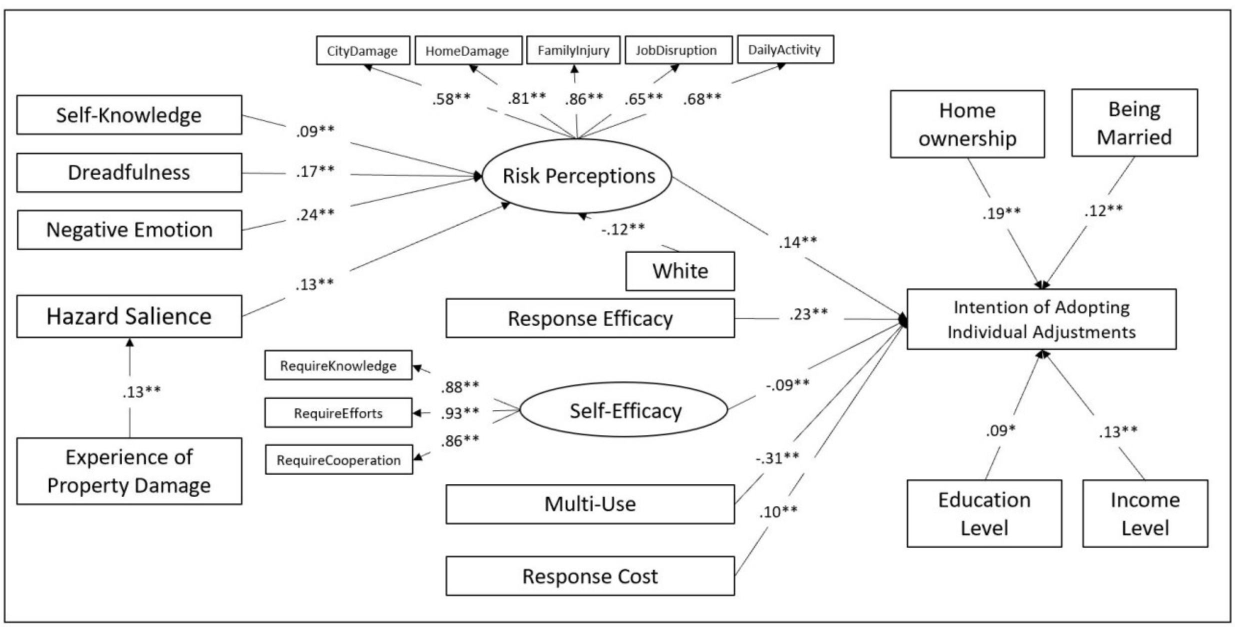

Figure B2: Grouped SEM Model Results (Complex)

Appendix C: Descriptive Statistics

Table C1: Descriptive Statistics*

Variables	M	S.D	α	Variables	M	S.D.	α	Variables	M	S.D.	α
Hazard Salience	2.51	0.79		SE_Knowledge_SP	2.15	1.21		RC_MultiUse_SP	3.36	1.31	
Property Damage	1.33	0.72		SE_Knowledge_SS	2.73	1.49	0.71	RC_MultiUse_SS	3.20	1.36	0.56
Self Knowledge	3.94	0.93		SE_Knowledge_HI	2.51	1.28		RC_MultiUse_HI	3.85	1.36	
Dreadfulness	2.61	1.12		SE_Knowledge_WR	1.92	1.13		RC_MultiUse_WR	3.43	1.37	
Negative Emotion	2.75	1.22		SE_Knowledge_SU	3.18	1.26		RC_MultiUse_SU	4.01	1.17	
RP_city damage	3.25	1.18		SE_Knowledge_EP	2.66	1.25		RC_MultiUse_EP	3.95	1.20	
RP_ home damage	2.63	1.03		SE_Knowledge_FL	1.52	1.07		RC_MultiUse_FL	4.29	1.17	
RP_family injury	2.17	1.05	0.86	SE_Knowledge_FE	2.83	1.24	0.86	RC_MultiUse_FE	4.26	1.13	0.88
RP_job disruption	2.25	1.15		SE_Knowledge_FAK	2.75	1.24		RC_MultiUse_FAK	4.40	1.02	
RP_activity disruption	2.56	1.16		SE_Knowledge_FAT	3.56	1.19		RC_MultiUse_FAT	4.47	0.94	
RE_ProtectPeople_SP	3.74	1.12		SE_Knowledge_TDF	1.97	1.17		RC_MultiUse_TDF	4.05	1.19	
RE_ProtectPeople_SS	4.58	0.76		SE_Knowledge_TDW	1.72	1.14		RC_MultiUse_TDW	4.08	1.24	
RE_ProtectPeople_HI	3.05	1.55		SE_Effort_SP	1.85	1.10		RC_CostMoney_SP	1.95	1.19	
RE_ProtectPeople_WR	3.87	1.09	0.77	SE_Effort_SS	3.07	1.38	0.65	RC_CostMoney_SS	3.98	1.03	0.54
RE_ProtectProperty_SP	2.64	1.37		SE_Effort_HI	2.33	1.20		RC_CostMoney_HI	3.87	1.00	
RE_ProtectProperty_SS	2.21	1.41		SE_Effort_WR	1.80	1.07		RC_CostMoney_WR	1.98	1.10	
RE_ProtectProperty_HI	3.87	1.26		SE_Effort_SU	2.55	1.20		RC_CostMoney_SU	1.57	1.05	
RE_ProtectProperty_WR	2.39	1.39		SE_Effort_EP	2.59	1.23		RC_CostMoney_EP	1.57	1.04	
RE_ProtectPeople_SU	4.17	1.04		SE_Effort_FL	1.46	0.99		RC_CostMoney_FL	1.59	1.00	
RE_ProtectPeople_EP	4.18	0.97		SE_Effort_FE	2.24	1.18	0.89	RC_CostMoney_FE	2.54	1.11	0.88
RE_ProtectPeople_FL	3.72	1.26		SE_Effort_FAK	2.15	1.13		RC_CostMoney_FAK	2.20	1.10	
RE_ProtectPeople_FE	4.23	0.97		SE_Effort_FAT	3.20	1.20		RC_CostMoney_FAT	2.55	1.11	
RE_ProtectPeople_FAK	4.14	1.01		SE_Effort_TDW	2.48	1.28		RC_CostMoney_TDF	2.70	1.19	
RE_ProtectPeople_FAT	4.25	0.98		SE_Effort_TDF	2.12	1.24		RC_CostMoney_TDW	2.09	1.17	
RE_ProtectPeople_TDF	3.98	1.13		SE_Cooperation_SP	2.00	1.21		Intention_SP	3.88	1.45	
RE_ProtectPeople_TDW	4.20	1.11	0.91	SE_Cooperation_SS	2.64	1.41	0.73	Intention_SS	3.61	1.54	0.62
RE_ProtectProperty_SU	4.17	1.03		SE_Cooperation_HI	2.23	1.22		Intention_HI	4.37	1.25	
RE_ProtectProperty_EP	2.82	1.45		SE_Cooperation_WR	1.76	1.12		Intention_WR	3.79	1.50	
RE_ProtectProperty_FL	2.67	1.52		SE_Cooperation_SU	2.32	1.30		Intention_SU	4.22	1.20	
RE_ProtectProperty_FE	4.25	0.94		SE_Cooperation_EP	3.11	1.34		Intention_EP	3.79	1.36	
RE_ProtectProperty_FAK	1.91	1.42		SE_Cooperation_FL	1.50	1.05		Intention_FL	4.75	0.80	
RE_ProtectProperty_FAT	2.01	1.44		SE_Cooperation_FE	1.96	1.22	0.89	Intention_FE	4.25	1.23	0.81
RE_ProtectProperty_TDF	1.82	1.34		SE_Cooperation_FAK	2.05	1.22		Intention_FAK	4.49	1.05	
RE_ProtectProperty_TDW	1.91	1.44		SE_Cooperation_FAT	2.83	1.32		Intention_FAT	3.89	1.36	
				SE_Cooperation_TDF	2.21	1.32		Intention_TDF	3.67	1.43	
				SE_Cooperation_TDW	1.91	1.25		Intention_TDW	3.84	1.40	

*M=mean; S.D.= standard deviation, α = Cronbach's alpha, RP = Risk Perception, RE = Response Efficacy, SE = Self-efficacy, RC = Response Cost, SP = Signing Up for Smartphone Alert; SS = Installing Storm Shelter, HI = Purchase Home Insurance, WR = Having a Weather Radio, SU = Shut Off Utility, EP = Develop An Emergency Plan, FL = Having A Flashlight, FE = Having A Fire Extinguisher, FAK = Having A First-aid Kit, FAT = Attending the First-aid Training, TDF = Store Three Day of Food, TDW = Store Three Day of Water.
*MultiUse is reversed, RC_MultiUse means lack of usefulness for other hazards.

Table C2: Descriptive Statistics Continued

	Basic Adjustments		Complex (Tornado-Specific) Adjustments	
Variables	M	S.D.	M	S.D.
RE	3.41	0.78	3.29	0.78
SE_RequireKnowledge	2.53	0.84	2.32	0.94
SE_RequireEfforts	2.35	0.88	2.25	0.86
SE_RequireCooperation	2.25	0.94	2.14	0.92
RC_MultiUse	1.79	0.83	2.54	0.88
RC_CostMoney	2.10	0.81	2.94	0.70
Intention	4.11	0.81	3.92	0.98

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