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Calibrating the Wildfire Decision Model using Hybrid Choice Modelling

Lovreglio R, Kuligowski E, Walpole E, Link E, Gwynne S

Abstract

Wildfire occurrences is creating serious challenges for fire and emergency response services and a diverse range of communities around the world due to the increment of the occurrence of these disasters. As such, understanding the physical and social dynamics characterizing wildfires events is paramount to reduce the risk of these natural disasters. As such, one of the main challenges is to understand how households perceive wildfires and respond to them as part of the evacuation process.

In this work, the Wildfire Decision Model originally proposed in [1] is calibrated using a hybrid choice model formulation. The Wildfire Decision Model is a newly developed behavioural choice model for large-scale wildfire evacuations based on the estimation of the risk perceived by households and the impact that this has on the decision-making process. This model is calibrated using a hybrid choice modelling solution and survey data collected after the 2016 Chimney Tops 2 wildfire in Tennessee, USA. The proposed model shows good agreement with the preliminary findings available in the wildfire evacuation literature; namely, the perceived risk is affected by both external factors (i.e., warnings and fire cues) and internal factors (i.e., education, previous wildfire evacuation experience and time of residency in a property).

Keyword: Household; Evacuation; Wildfire; Hybrid Choice; Modelling

1. Introduction

The wildfire threat is a growing concern for many rural and urban areas all around the world [2], [3]. Statistical evidence indicates that wildfire occurrences have increased in the last three decades, creating several major challenges for fire and emergency response services and a range of diverse communities around the world [4]–[6].

To enhance the safety of communities threatened by wildfire and reduce the risk of wildfire, it is imporatnt to investigate and unveil the physical and social dynamics characterizing wildfire events – including how a community responds to the evolving conditions faced [1]. Several efforts have been made to address this challenge and several wildfire models and evacuation models have been proposed in the literature. Wildfire models can divide into empirical, semi-empirical and physical models [7]. While physical models represent the most flexible and advanced solution, their use is limited by the computational costs required to run simulations. As such, fire and emergency agencies often prefer using empirical and semi-empirical wildfire models. From an evacuation point of view, models can be divided into conceptual and engineering models [8]. The former models identify the behavioural steps householders go through when assessing and responding to wildfire emergencies. The latter models can instead sub divided into choice and traffic models. Choice models are tools allowing users to predict how and/or when humans will respond to a wildfire. On the other hand, traffic models allow users to predict microscopic or macroscopic traffic conditions during a wildfire evacuation.

The literature shows that 22 traffic tools can be used to simulate the pedestrian and traffic evacuation dynamics of communities affected by wildfires. These models can be used for evacuation planning and real-time decision support during emergencies [9], [10]. Furthers, these modelling solutions present different features when focusing on fire-related, spatial, and demographic factors and can be selected depending on the spatial scale and simulation time of specific case studies [7], [9]. A comprehensive review of these modelling solutions and tools is available in [7], [9], [11]. Most of these models were originally developed to simulate traffic in non-emergency conditions and have been adapted to simulate wildfire evacuation conditions (see for instance [12]–[16]). As such, these tools are limited in their ability to realistically simulate household decision-making in wildfire evacuations. In fact, most of the household decisions associated with evacuation (such as trip generation and distribution) are input for these simulation tools rather than being an output.

To date, one of the main challenges to simulate wildfire evacuation is to understand how households perceive wildfires (e.g., associated cues and information, the threat itself and the risk associated with these events) and in turn, respond to them [17]. Several behavioural studies have been carried out to investigate household decision making in wildfires using data from several countries around the world [18]. These studies propose several choice models showing how different factors can impact the householder decision to stay or evacuate when facing a wildfire.

For instance, Toledo et al. [19] used discrete choice analysis to understand actual behavior in wildfires in Israel while Lovreglio et al. [1] and Strahan et al. [20] used this modelling solution to predict the evacuation decision of Australian householders. Further implementations have been carried out using data from US, see for instance the work by MCaffrey et al. [21] and Wong et al. [22].

Many of these behavioural studies were reviewed by Folk et al. [17] to identify the factors affecting household perceptions and response to wildfire. Based on these findings, a mathematical framework modelling those decision-making processes was proposed by Lovreglio et al. [1]: the Wildfire Decision Model (WDM). The WDM aims to generate new dynamic travel demand models for large-scale wildfire evacuations by estimating the risk perceived by households and, in turn, their behavioural states at each time step in the evacuation process. However, only part of the WDM has been calibrated in the original article predicting the decision to stay or evacuate [1]. Due to the lack of suitable data, the calibration of the risk perception component of the WDM has not been tested. As such, the WDM model can only be used to predict the decision to stay or evacuate while it is not suitable to predict how and when households change behaviour state and start evacuating, as calibrated parameters were not provided in [1].

This paper presents a calibration solution for the WDM using hybrid choice modelling. Hybrid Choice Models (HCMs) represent an extension of the classic random utility model, which are commonly used to investigate a human choice among a set of discrete alternatives. HCMs enhance utility models by integrating latent psychological variables in choice models, using a structural equation formulation [23]–[25]. As such, HCMs provide the possibilities to estimate the risk perceived by a household and how this risk affects their wildfire response (e.g., when they evacuate). In this paper, the calibration of the WDM was conducted using survey data collected after the 2016 Chimney Tops 2 fire in Tennessee, USA (Walpole and Kuligowski, 2020). Using mail and online contact methods, the questionnaire assessed the types of warnings and fire cues received by households, their risk perceptions at various time points in the evacuation, and evacuation decisions and actions taken in response to the wildfire event. Additional information on the questionnaire is provided in Section 3 of this article.

2. Material and Methods

In this work, the WDM is calibrated using a hybrid choice formulation. The behavioural and theoretical assumptions underpinning the WDM are introduced in Section 2.1. The hybrid choice formulation to estimate this model is introduced in Section 2.2.

2.1 Modelling Assumptions

The WDM provides a simplified version of the Protective Action Decision Model introduced by Lindell and Perry [26] and is based on the Evacuation Decision Model proposed by Reneke [27] and expanded by Lovreglio et al. [28], [29]. The WDM relies on several assumptions, which are summarized below.

1. The main factor used to predict the decision to take protective actions as well as the time required for such a decision is the perceived risk of householders.

2. Householders are categorized as in one of four behavioural states:
    a. *Normal State* - Householders have not perceived any risk or they have a relatively low level of risk, and continue routine activities thinking that there is no credible threat.
    b. *Investigating State* – Householders may be uncertain about the nature/significance of the threat, but perceive some risk, and seek additional information to clarify the situation.
    c. *Vigilant State* – Householders have identified a credible threat but keep gathering information before taking a decision on whether or not to take protective action and what this action might be. As such, householders in this state "tend to carry out fewer preparations both for defending and for evacuating compared with people who have decided on one of these concrete actions" [30].
    d. *Protective State* – Householders take protective action, choosing between several possible strategies, and respond accordingly.

3. Householders take actions using one or a combination of protective strategies such as stay - defend, stay - shelter, or leave. "Stay - defend" is defined as an action used to protect a householder's property and/or its occupants. When households decide to "Stay - shelter" (or shelter in place; SIP), they do not attempt to regularly monitor conditions inside and outside of the shelter and they do not take any defensive actions; in this case, householders use their property for protection only.

4. The change in perceived risk is assumed proportional to the cumulative intensity of external factors the householder receives (i.e., physical and social cues and the information sources) and the householder's internal factors (i.e., socio-demographic, perceptions, and memories of previous experiences and attitudes).

5. The effects on perception of risk of the external and internal factors are additive and subtractive according to a linear formulation.

6. Both external and internal factors have impacts on the choice of actions and strategies taken at each behavioural stage.

7. The level of perceived risk of households facing the same wildfire event may not be equal, as householders might perceive and assess the same emergency scenario in different ways. This is in line with the concept of behavioural uncertainty, which is defined as the impossibility for an external observer to achieve deterministic knowledge of an evacuation process given the complexity of the decision-making process [31], [32]. To address such a challenge, stochastic or semi stochastic modelling solutions are suggested to develop wildfire evacuation models [11] and are used here.

The conceptual model of the WDM integrating all the assumptions is illustrated in Figure 1.

Several discrete choice models have been proposed to predict protective actions (i.e., stay-defend, stay-shelter, or leave) using different datasets from the US [21], [33], [34], Australia [1], [20], [35], [36], and Israel [19]. To date, there is no published model capable of predicting the behavioural states of the WDM. However. Several studies are available that show which external and internal factors influence risk perception as highlighted in a recent literature review [17]. A list of these factors is provided in Table 1.

The factors in Table 1 include both external and internal factors that have been identified in wildfire evacuation literature as influencing levels of risk perception. The external factors include witnessing cues from the fire like smoke, embers or firebrands and flames; being located within close proximity to the fire (especially if the fire is more intense in size, rate of spread, and/or heat production); observing others in the area evacuating; and receiving a warning or order to evacuate. The literature has found positive relationships between the external factors in Table 1 and levels of risk perception. The internal factors identified include respondent's age, household income, level of education, gender, length of time that the household has been living at a residence, whether or not the household has experienced damage in a previous wildfire event, whether or not a household has experience in a previous wildfire (e.g., have they evacuated in a wildfire before), and whether or not the household is located in a suburban area. Table 1 shows the signs for the relationships between each of these variables and levels of perceived risk, as well as reference sources for each finding.

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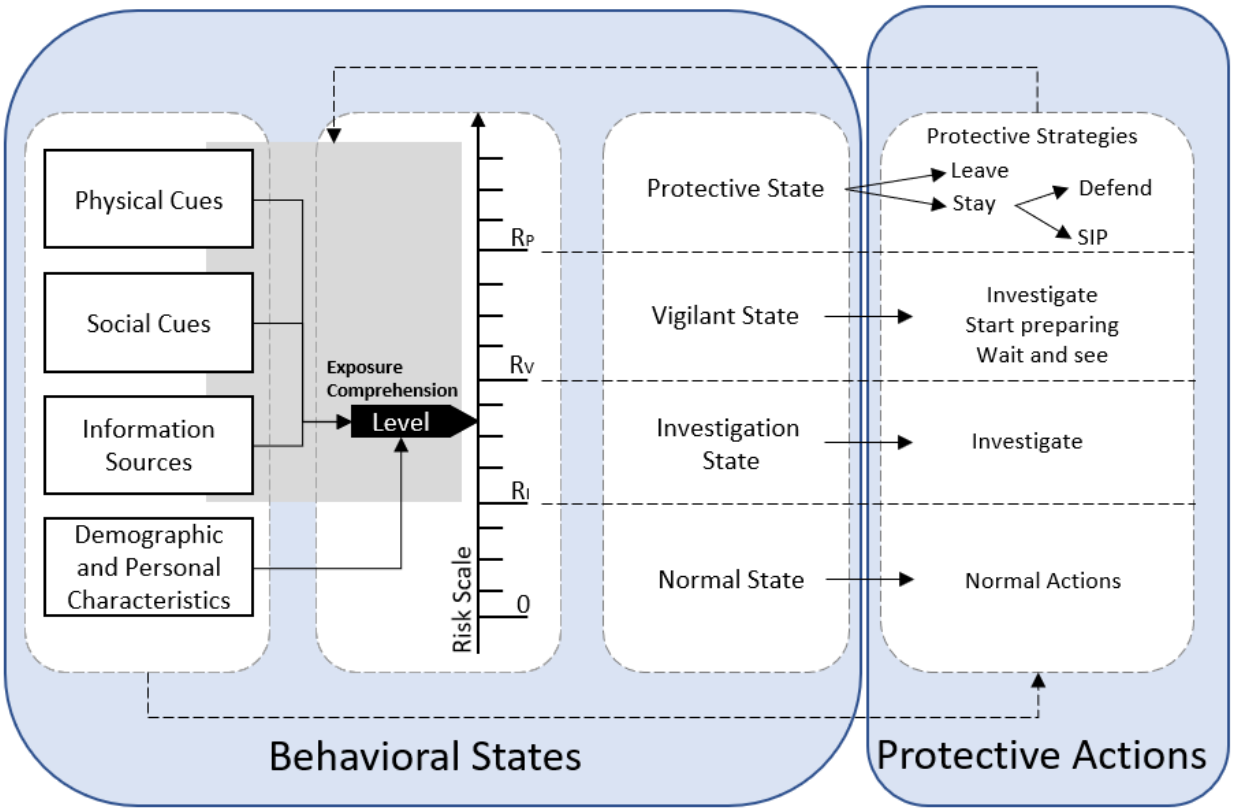

Figure 1 – Conceptual model of the WDM. This figure is a modified version of the original figure in [1]. (R_I, R_v, and R_p are the risk thresholds to pass from a behavioural state to another)

Table 1 – The list of external and internal factors affecting households risk perception (note: "+" indicates a positive impact; "–" indicates a negative impact). This table is an expanded version of the table published in [1].

Factor	External	Internal	Reference
Visible smoke	+		[37], [38]
Embers/Firebrands	+		[37], [38]
Flames	+		[37], [38]
Fire proximity and intensity	+		[37], [38]
Observation of others leaving	+		[37]
Evacuation warning/order	+		[39]
Age		–	[17]
Income		+	[33]
Level of Education		+	[39]
Gender (female)		+	[39]
Residence time		–	[33], [39]
Previous property damage		+	[39]
Previous experience		+	[39], [40]
Living in suburbs		–	[41]

2.2 Hybrid Choice Models

Hybrid Choice Models (HCM) represent an extension of standard discrete choice models, which include binomial, multinomial, and ordered logit models. In contrast to others, HCM allows latent psychological variables to be incorporated into discrete choice models [23]–[25]. This is achieved by a combination of structural and measurement equations. A general formulation for this modelling solution is provided by Walker and Ben-Akiva [24]. We adopt such a formulation to represent the WDM.

The WDM proposed in this work has a single latent variable: the risk perceived by the *h* householder (R_h). Depending on their perceived risk, the *h* householder will fall into one of the four behavioural states S_h={1: Normal; 2: Investigation; 3: Vigilant; 4: Protective}. Following the annotation proposed in [25], the structural and measurement equations can be written as outlined in Section 2.2.1 and 2.2.2. The proposed HCM solution for the WDM is illustrated in Figure 2, and the equations are explained in further detail below. It is worth clarifying that the most generalized version of HCM proposed in the literature [19]–[21] provides a formulation in which multiple latent and explanatory variables are directly affecting the utility function. In this work, a specific case of HCM was instead implemented including only a single latent construct (i.e. the perceived risk; R in Figure 2). This was done to follow the conceptual modelling structure provided in the existing literature on evacuation decision-making [1], [23].

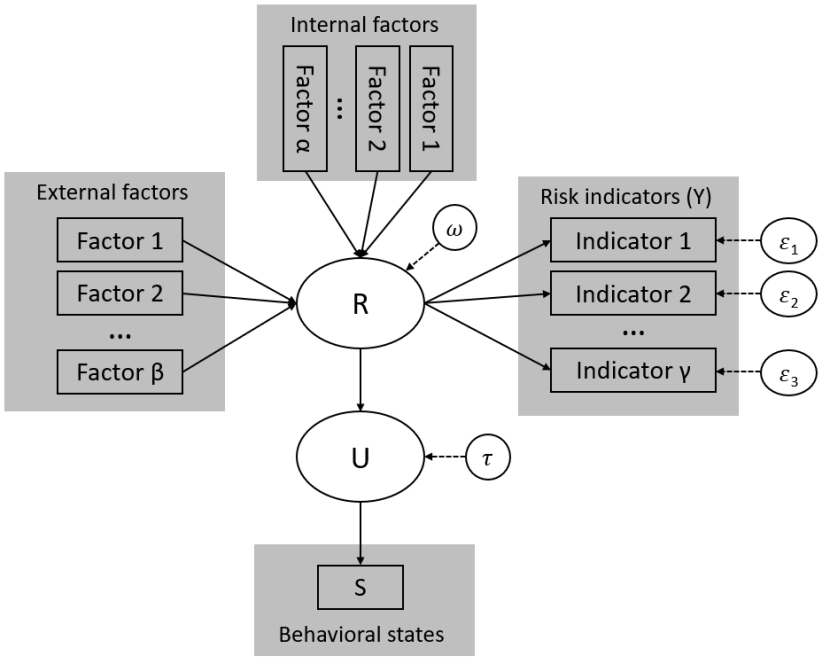

Figure 2 – HCM structure for the WDM.

2.2.1 Structural equations

Equation 1 is the structural equation linking the perceived risk of the *h* householder (R_h) to their external factors E_h and internal factors I_h. While R_h is scalar quantity, E_h is a (1 X α) vector identifying the α external factors and I_h is a (1 X β) vector identifying the β internal factors. Accordingly, b_E and b_i are the respective (1 X α) and (1 X β) vectors defining the weight of each internal and external factors on the risk perception. Finally, the risk perception has an ω error component which is usually distributed with mean equal to zero and standard deviation equal to σ_R.

$$R_h = b_E \cdot E_h + b_i \cdot I_h + \omega, \quad \omega \sim N(0, \sigma_R) \qquad \text{Equation 1}$$

Equation 2 is the structural equation linking the perceived risk and the utility (U_h) required to pass from one behavioural state to another behavioural state. ρ is a scalar quantity defining the weight of the perceived risk. Finally, the utility has an τ error component which has a logistic distribution with mean equal to zero and standard deviation equal to 1.

$$U_h = \rho\, R_h + \tau, \quad \tau \sim L(0,1) \qquad \text{Equation 2}$$

2.2.2 Measurement equations

Equation 3 is the measurement equation linking the perceived risk to the Y_h indicators measuring the risk perceived by the *h* householder. In this work, these are measured using a Likert scale

approach, as explained in Section 3.4.1. Y_h corresponds to a (1 X γ) vector while b_r is (1 X γ) vector defining the weight of the perceived risk where γ is the number of indicators measuring the perceived risk. Finally, there is a (1 X γ) vector of normally distributed error components, ε, having a mean equal to zero a Ω covariance matrix.

$$Y_h = b_r R_h + \varepsilon, \quad \varepsilon \sim N(0, \Omega) \qquad \text{Equation 3}$$

Equation 4 is the measurement equation linking the utility of the *h* householder to their behavioural state (S_h).

$$S_h = \begin{cases} 1 & U_h < \mu_1 \\ 2 & \\ 3 & if \ \mu_1 < U_h < \mu_2 \\ 4 & \mu_2 < U_h < \mu_3 \\ & \mu_3 < U_h \end{cases} \qquad \text{Equation 4}$$

The parameters in Equations 1-4 can be calibrated using data from wildfire evacuation studies. This can be achieved by asking respondents to state their level of perceived risk at the moment when they perceived any cue or received a warning and then by asking them to identify their subsequent wildfire response. Next section illustrates how this can be done using the case study of the Chimney Tops 2 fire.

3. Model Calibration

3.1. Chimney Tops 2 fire

On November 23rd, 2016 the Chimney Tops 2 fire started in the Great Smoky Mountains National Park in Tennessee. Driven by high winds and drought conditions, the fire reached the City of Gatlinburg and surrounding areas on the evening of November 28th. Around noon on the 28th, first responders had begun disseminating voluntary evacuation notices in targeted neighbourhoods; however, following rapidly changing fire conditions a mandatory evacuation notice was issued for Gatlinburg and the surrounding areas at approximately 6 pm.

Between 6pm and 10 pm, approximately 14,000 tourists and residents were then evacuated from the area [42], [43]. Unfortunately, due to power losses, the loss of communication services, and miscommunication between state and local organizations, the remote dissemination of warnings via platforms such as reverse-9-1-1 and wireless emergency alerts (WEAs) was disrupted or delayed. However, fire and police officials conducted door-to-door evacuations. In total, the fire burned 17,000 acres and resulted in the loss of 14 lives and damage to approximately 2,500 structures [38].

3.2 Questionnaire

The survey instrument[1] was intended to measure a variety of factors found to be influential on evacuation decisions in the literature. Items were primarily developed based on three wildfire evacuation surveys from the U.S. [44] and Australia [20], [45] (McLennan 2012; Strahan 2018), and a survey to study an evacuation related to a dam break [46].

The survey began with the measurement of several pre-event variables such as prior awareness of wildfire risks in the area and previous experience with evacuations. However, the bulk of the survey consisted of several skip-logic questions and resulting items related to warnings or fire cues individuals may have received leading up to their evacuation decision, as well as associated risk perceptions and actions. Namely, respondents were asked: "*Did you receive any warnings about a wildfire occurring that could threaten your town/city or residential area?*", and if yes, they were prompted to answer other questions related to the time, type, and source of these warnings, among other items. Respondents were also asked whether they received "*Any information about the Chimney Tops 2 fire from the fire itself, e.g., seeing, hearing, feeling, or smelling the fire such as flames, smoke, embers, etc.?*", and if yes, they were prompted to answer other questions related to the location, time, and type of fire cue (e.g. flames, embers, and/or smoke).

At the end of both the warnings and fire cues sections, participants were asked how threatened they felt immediately after receiving the warning or fire cue, using four items adapted from the US Army Corps of Engineers (ACE) survey [46] and what their immediate response was. See Walpole and Kuligowski (2020), Appendix A, for a copy of the questionnaire used in this study.

The survey ended with a series of questions related to participants' evacuation decisions and the main drivers behind choosing to stay, delay, or evacuate, as well as socio-demographics variables, including gender, age, education level, income, and length of residence in the area, among others. Due to a high prevalence of "refuse" responses, 62 missing income values were inputed using a penalized regression with the Glmn function in the R software package[2]. Namely, a lasso penalty was used to control overfitting in a multinomial regression model fitting income by the following predictors: age, education, and gender.

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[1] The survey and associated data analysis received IRB approval through an expedited review by the National Institute of Standards and Technology Institutional Review Board (IRB), and all participants were requested to provide their informed consent before participating in the survey.

[2] Certain commercial entities, equipment, or materials may be identified in this document in order to describe an experimental procedure or concept adequately. Such identification is not intended to imply recommendation or endorsement by the National Institute of Standards and Technology, nor is it intended to imply that the entities, materials, or equipment are necessarily the best available for the purpose.

Lastly, due to privacy concerns, participant location data was provided by a contractor in the form of census blocks. Specifically, participants provided the contractor with their home addresses at the time of the fire as part of the survey; the contractor then verified and converted this information into census blocks.

3.3 Participant Sample

For the purposes of the survey, it was desirable to contact as many individuals as possible who had experienced the Chimney Tops 2 fire and made subsequent evacuation or property defense decisions, focused on residents who had lived in the area full or part-time. This approach did not include tourists and vacationers, who may have also experienced the fire but were less in a position to take preparatory or home-defense actions in response. To do this, both mail and online sampling approaches were utilized by a survey research firm (Fors Marsh Group located in Virginia, USA) between October 29, 2018 and May 22, 2019.

First, the mail and phone-based sample frame consisted of households with available addresses within the fire-affected areas (defined as census blocks located within or touching the burned area), as well as neighbourhoods noted in public evacuation notices. This approach yielded a list of 3,997 addresses, which were sent an initial invitation letter inviting the head of the household to complete the survey online. Those who did not complete the online survey were mailed up to two reminder postcards, and households with available phone numbers (n = 1,996) were also given up to five call reminders (during which they could complete the survey via phone if they preferred), which yielded 210 completed responses. Second, in an effort to also reach individuals who might have moved away from the area or lost their homes as a result of the fire (and thus would not be accessible in a mailed survey) a targeted online advertising campaign was conducted focused around the Gatlinburg, TN area. Specifically, advertisements for the survey were placed in local newspapers and news websites and were also placed on Facebook targeted at users within a 15-mile radius of Gatlinburg, TN, which yielded an additional 178 responses. In total, 388 participants completed surveys online or via phone. See Figure 3, below, for a map of the Gatlinburg area, including the burned area and the frequency distribution of all survey respondents.

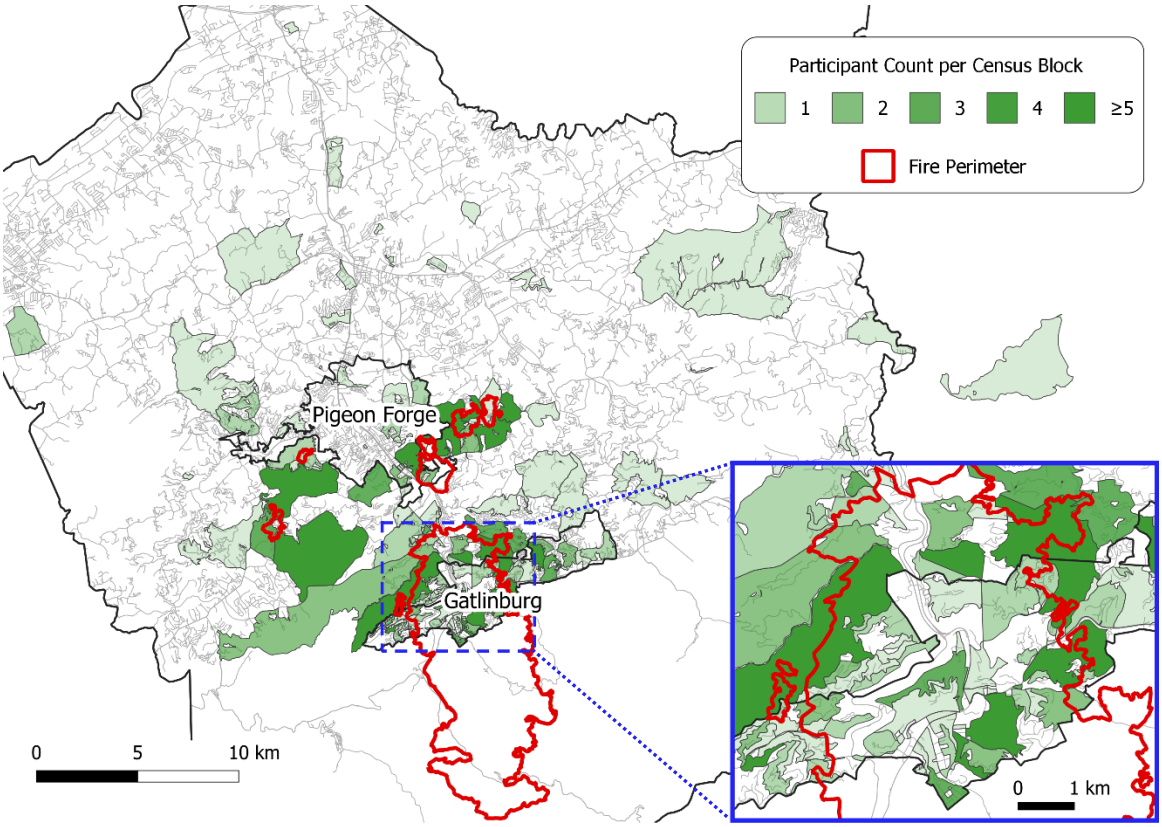

Figure 3. Locations of survey respondents defined by census block. The inset shows a zoom of the downtown area of Gatlinburg.

To create our sample used in the HCM model reported below, we first removed those who reported they were at work or otherwise not at home during the event (because the location data provided was home address (n = 24). To further clean the dataset, we also removed those who had missing data related to the variables in the model. This included if they received a warning but didn't include their risk perceptions, response, or the date of the warning (n = 12) if they received a cue but didn't including their risk perceptions, response, or the date of the cue (n=14), those who reported receiving neither warnings nor cues (and therefore would have missing data on the above-mentioned variables (n = 91) and lastly we removed those remaining in the dataset who had not provided their home location data (n = 11). Following these measures, we were left with a final sample size of 236.

Among this sub-sample, participants were 56.8% female, with a median age of 55 years to 64 years, and a median income of $35,000 to $49,999. A majority of the sample had also lived in the area for 5 or more years (17.8% for 5 years to 10 years and 50.0% for 10+ years).

3.4 Data Structure

Given the structure of the questionnaire, the participants were given the possibility to report both their perceived risk and their wildfire response two times[3]: 1) when they received the first warning and 2) when they perceived a fire cue. The data indicates that only 41 of 236 respondents received a warning and perceived at least one fire cue. As such, it is possible to obtain a total of 277 observations (1x195 + 2x41).

3.4.1 Risk Indicators

The respondents were asked to report their level of risk perception by answering four Likert scale questions in response to the receipt of warnings and/or cues. The Likert scale items assessing the levels of risk perception are:

Risk question 1: I might become injured
Risk question 2: Other people/pets/livestock might become injured
Risk question 3: I might die
Risk question 4: Other people/pets/livestock might die

For each of these questions, the participants were asked to report their level of likelihood using a five-point scale (1: not likely and 5: extremely likely).

3.4.2 Behavioural State

The question assessing their response after the warnings and fire cues was the following, including five possible response options:

What was your immediate reaction?

a) No reaction; I continued my activities
b) I waited for more information
c) I tried to find more information
d) I started preparing to act and then waited for further information
e) I took action immediately (e.g., evacuated/left the location, defended my property, took shelter, etc.).

Given the behavioural states in Section 2.1, it is possible to assume that participants were in one of the following, based on the response options (a-e) above:

[3] Participants were also asked to identify their level of perceived risk at the time of the evacuation decision (i.e., evacuation or stay). However, these measurements are not used in this calibration as they are not associated with a respondent's behavioural state (see Section 3.4.2).

1) Normal State if they answer (a);
2) Investigate State if they answer (b) and (c);
3) Vigilant State if they answer (d);
4) Response State if they answer (e).

Given that the behavioural states can be represented by an ordinal variable ranging from 1 to 4, this represents the choice variable that is predicted in this work in Section 3.5.2 using the ordinal logit formulation in Equation 3 and 4.

3.4.3 External Factors

Several questions were asked to assess whether participants had received any type of warning and/or perceived any fire cues. As such, it is possible to identify three dummy variables assessing whether participants had received any warning(s), cues in the form of flames, or cues in the form of embers on the 28th of November 2016 (the day in which the wildfire spread to Gatlinburg, TN and surrounding areas).

Another important external factor was the proximity of the participants from the wildfire front. This distance was measured as a straight line from each survey participant's initial location to the nearest possible point on the final fire perimeter as the data regarding the evolution of the perimeter overtime is not available. The precise location of participants within their census blocks was not known; therefore, the centroid of each block was used as the starting point of the distance measurements. Fragments of the fire perimeter data that created spot fires less than 5 acres in the area were considered as noise and were removed. The nearest distance measurement from the fire perimeter to each census block centroid is shown in Fig. 4. Centroids located within the fire perimeter were defined as zero distance.

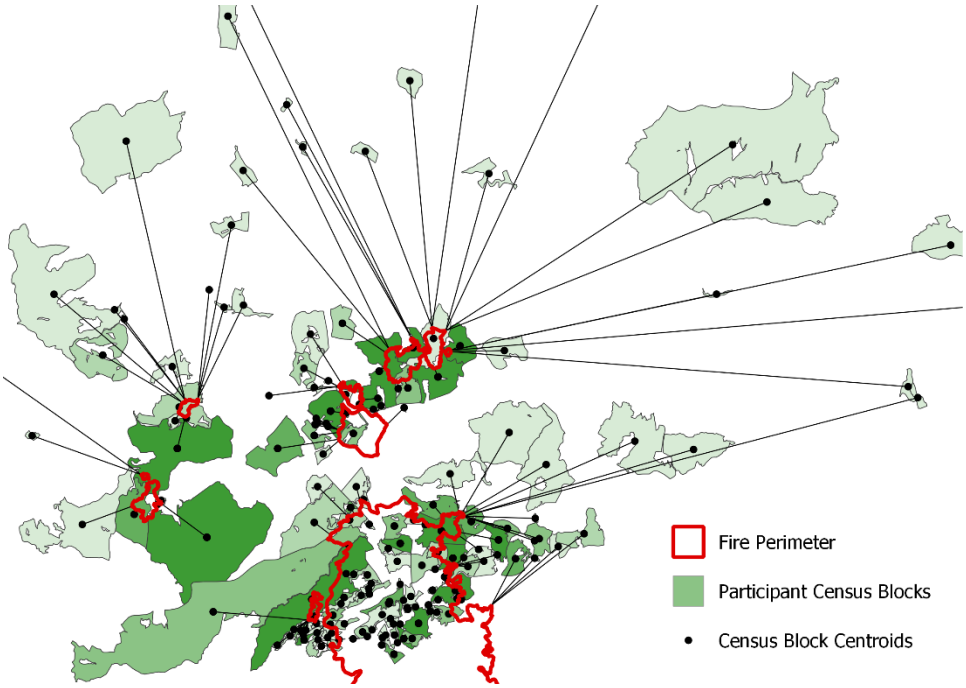

Figure 4. Proximity of participants from the fire was measured from the centroid of each participant's census block to the nearest edge of the final fire perimeter.

3.4.4 Internal Factors

Several questions were asked to measure the socio-demographics of the participants using closed-ended questions with multiple response options (i.e., from two to up to nine options). To generate a simple model capable of verifying the impact of all the selected variables on the risk perceptions (i.e., parsimonious model), some of the demographic variables were recoded as simple dummy variables. This recoding was done to avoid the overuse of dummy variables to account for a single factor. Also, the recoding was completed such that the sample could be split into groups each accounting for 40% to 60% of the sample and using the following criteria:

-Age: 1 if the householder's age was above 65 (retirement age in the U.S.) and 0 otherwise;
-Education: 1 if the householder did not hold Bachelor or Graduate degree and 0 otherwise;
-Income: 1 if the household income was below 50k USD and 0 otherwise;
-Residence: 1 if the household had been living at that residence for more than 10 years and 0 otherwise.

Finally, it was possible to measure if the participants were living in the city centre of Gatlinburg or in a suburb or rural area by measuring the distance of their census block to the centre of Gatlinburg; Figure 5 illustrates this distance.

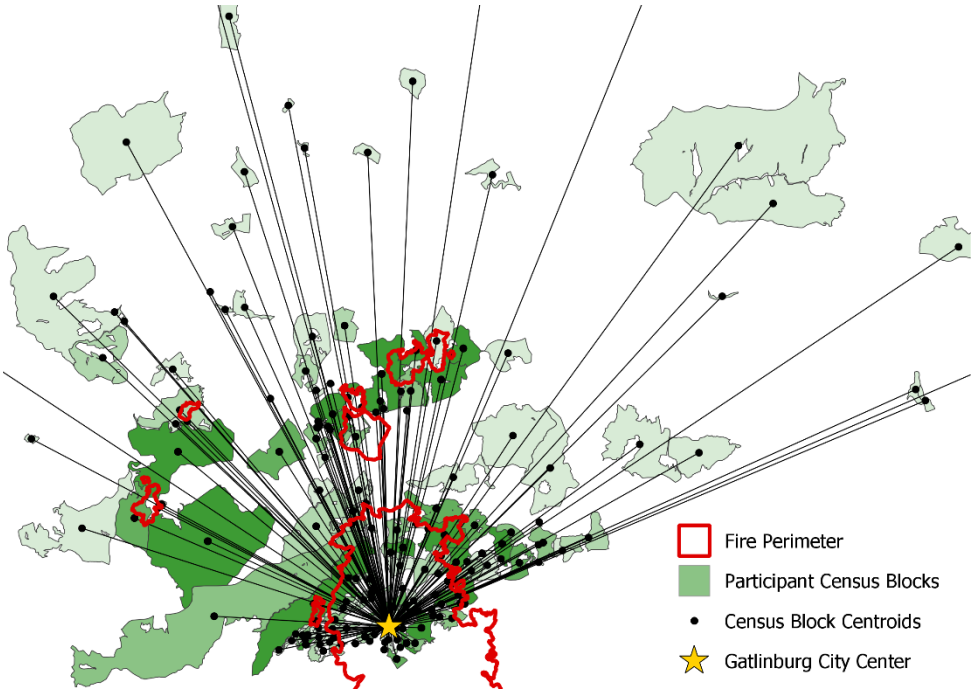

Figure 5. Proximity of participants to the Gatlinburg city center, measured from the centroid of each census block.

3.5 Model Specification and Estimation

The hybrid choice model proposed in this paper is estimated using a sequential approach. The structural and measurement components related to the risk model (i.e., Equation 1 and 3) are estimated in the first step with a likelihood optimization approach using AMOS Version 26[2]. The estimated model is then used to predict the risk perception for each householder. The structural and measurement components related to the utility and behavioural states model (i.e., Equation 2 and 4) are estimated in a second step using the results generated in the first step (i.e., the prediction of the risk perception for each householder). The second calibration was run in SPSS Version 26 using a likelihood optimization approach. The model specification of the HCM is represented in Figure 6. The model specification includes most of the factors in Table 1 except for factors that were not measured with the questionnaire, such as “observation of others leaving” and “previous property damage”. Finally, smoke visibility was also excluded as the smoke was visible many days before the emergency started.

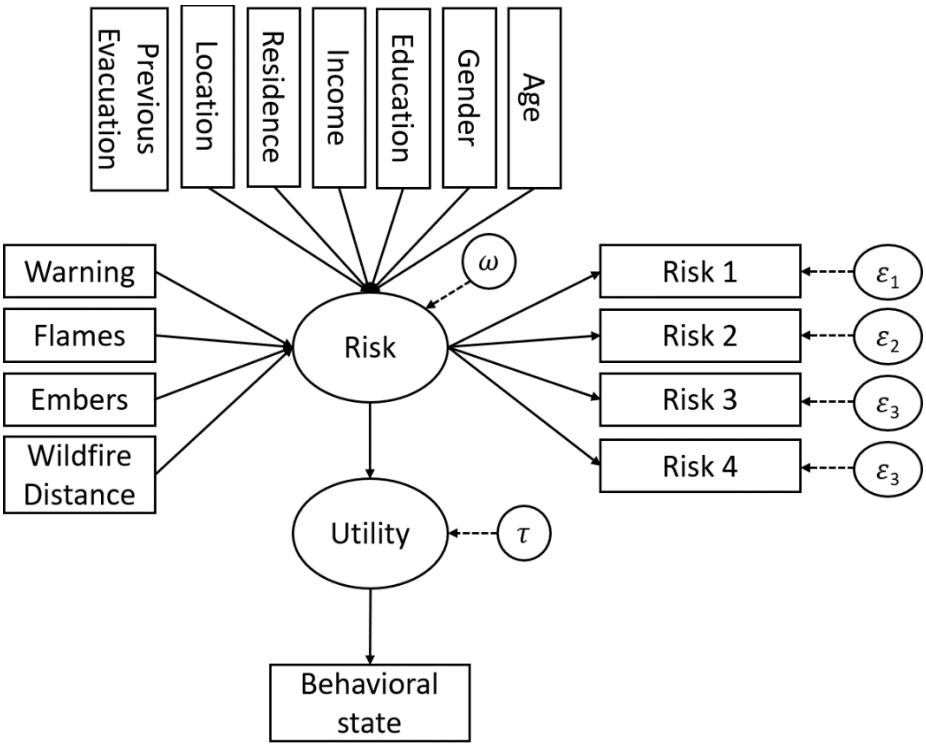

Figure 6 – HCM specification (Readers can refer to Section 3.4.1 for the definition of Risk 1-4 and to Table 2 for the definition of the remaining variables).

3.5.1 Risk Model

The estimated parameters for the risk model are reported in Table 2. Since household risk is the key variable affecting the passage from one behavioural state to another, as illustrated in Section 2.1, this model is used to identify the factors that influence the latent variable (risk perception). The model fit shows that the chi-square test is not statistically significant (p-value < 0.05). This is justified by the fact that this test is sensitive to the number of observations, and the number of observation is greater than 100 [47]. As such, other fitting parameters are normally used to assess the goodness of fit of structural equation models, such as the Comparative Fit Index (CFI) and Root Mean Square Error of Approximation (RMSEA). CFI and RMSEA can range between 0.0 and 1.0, with values closer to 1.0 indicating a good fit for CFI and closer to 0.0 for RMSEA. As shown in Table 2, the CFI is greater than 0.9, and the RMSEA is smaller than 0.1. Given the established cut-off values in the literature [47]–[49], the proposed model shows a relatively good fit.[4]

The majority of the regression weights defining the relationships expressed in Equations 1 and 3 are statically significant, assuming a significance level of 0.1. The weights which are not significant are those related to the wildfire distance, gender, age, location, and income. The signs of the statistically significant weights are all in line with the expected signs illustrated in Table 1.

[4] A reader should be aware that CFI and RMSEA are not stable as CFI punishes complex models while RMSEA reward complex models [47].

The structural part of the model also has several significant correlations between independent variables in the model, as well as a correlation between the error components of Risk 2 and Risk 3. All of the correlations have been identified through the modification indices, which captures "the evidence of misfit" and directions to improve the fitting of the model [50]. Finally, the model is capable of explaining more than 30% of the variance of the perceived risk and well above 45% of the variance of the risk indicators, shown by the squared multiple correlation values in Table 2.

Table 2 – Risk model parameters estimation.

Model Fit			
Observations = 278 Degrees of freedom = 77 Chi-square = 128.635 - p-value = 0.000 CFI = 0.904 RMSEA = 0.092			
Regression Weights			
Parameter	Definition	Estimate	p-value
Risk Intercept		1.000	fixed
Warning → Risk	1 if the householder received a warning from the 28th of November 2016; 0 otherwise	0. 738	0.009
Flames → Risk	1 if the householder saw flames; 0 otherwise	0. 927	0.000
Embers → Risk	1 if the householder saw embers; 0 otherwise	0. 794	0.000
Wildfire Dist. → Risk	Distance of the household from the wildfire in Km	-0.001	0. 987
Age → Risk	1 if the householder's age is above 65; 0 otherwise	-0.170	0. 570
Gender → Risk	1 if the householder is female; 0 otherwise	-0.114	0.658
Education → Risk	1 if the householder did not hold Bachelor or Graduate degree 0 otherwise	-0.487	0.081
Income → Risk	1 if the household income is below 50k USD; 0 otherwise	0.097	0.730
Residence → Risk	1 if the household has been living in the property for more than 10 years; 0 otherwise	-0.533	0.060
Location → Risk	Distance of the property from the city center	0.032	0.463
Prev. Evac. → Risk	1 if the household has experienced a previous evacuation; 0 otherwise	1.682	0.000
Risk → Risk1	I might become injured	1.000	fixed

	(1: not likely and 5: extremely likely)		
Risk → Risk2	Other people/pets/livestock might become injured (1: not likely and 5: extremely likely)	0.784	0.000
Risk → Risk3	I might die (1: not likely and 5: extremely likely)	0.917	0.000
Risk → Risk4	Other people/pets/livestock might die (1: not likely and 5: extremely likely)	0.772	0.000
Risk4 Intercept		1.773	0.000
Correlations			
Wildfire Distance ↔ Location		0.695	0.000
Flames ↔ Embers		0.341	0.000
Age ↔ Income		-0.420	0.000
Age ↔ Residence		0.234	0.000
Age ↔ Location		0.114	0.002
Education ↔ Residence		0.296	0.000
Education ↔ Gender		-0.370	0.000
Education ↔ Location		0.259	0.000
Residence ↔ Gender		-0.266	0.000
Residence ↔ Income		-0.249	0.000
Location ↔ Income		-0.196	0.000
Location ↔ Prev. Evac.		0.259	0.000
$\varepsilon_2 \leftrightarrow \varepsilon_4$		0.797	0.000
Squared Multiple Correlations			
Risk		0.311	
Risk1		0.486	
Risk2		0.842	
Risk3		0.520	
Risk4		0.951	

3.5.2 Utility Model

The estimated parameters for the utility and behavioural states model are reported in Table 3 using a logit link function (i.e., ordered logit formulation [51]). The chi-square test shows that the estimated model provides a better fit compared with the model having only an intercept (p-value = 0.000). Moreover, the cross-validation illustrates that the model is capable of predicting more than 54% of the chosen behavioural states. This model can also be used to simply classify if householders are responding or not; in this case, the model is capable of predicting 77% of this choice.

Finally, all of the parameters describing Equation 2 and 4 are statistically significant assuming a significance level of 0.1, and the sign of the parameter associated with Risk is in line with expectations (i.e., positive). This indicates that households will pass from the Normal State to the

Investigating, Vigilant, and Response States with each increment of their risk perception. A visualization of the results of the model in Table 3 is provided in Figure 7, assuming an arbitrary value for Risk of 1 and 2. The dashed lines defined by the μ_i thresholds in Figure 7 divides the chart into several sections: Normal, Investigating, Vigilant and Response. The probabilities of being in each behavioural state are the areas sustained by the logistic density function in each section. Figure 7 highlights that with the increase of Risk of households, the probability to the Response State increases (see the areas sustained by the logistic density function in the Response section of the chart). As such, the proposed model provides specific value to Figure 2 published in the original paper presenting the WDM [1].

Table 3 – Utility model parameters estimation.

Model Fit – Ordered Logit			
Observations = 278 Degrees of freedom = 1 -2 Loglikelihood Intercept Only = - 580.085 -2 Loglikelihood Final Model = - 460.507 Chi-square = 104.715 - p-value = 0.000 Cross Validation = 54%			
Parameter	Definition	Estimate	p-value
μ_1	Threshold between Normal and Investigate States	-0.936	0.000
μ_2	Threshold between Investigate and Vigilant States	1.606	0.000
μ_3	Threshold between Vigilant and Respond States	2.868	0.000
Risk	Latent risk perceived by householders	1.000	0.000

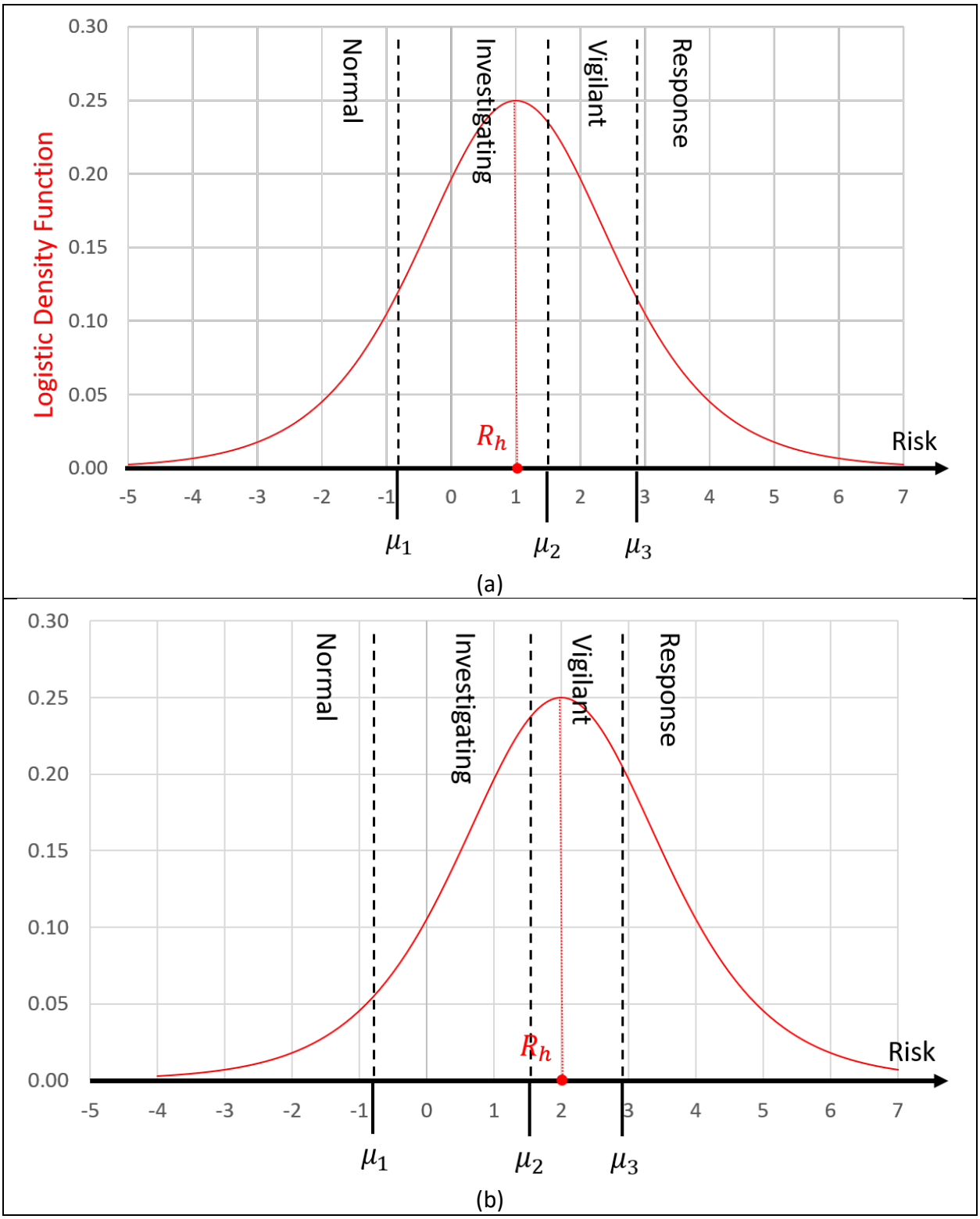

Figure 7 – Visualization of the Ordered Logit introduced in Table 3 assuming a Risk value of (a) one and (b) two (e.g. arbitrary number).

3.6 Model Implementation

The model described in Section 3.5 can be easily implemented to estimate the perceived risk and the behavioural state of householders affected by the Chimney Tops 2 given certain external conditions (i.e. if they receive at least one warning and see flames and embers). For instance, assuming that an individual has a Bachelor's degree and has been living less than 10 years on the property, it is possible to measure his/her risk perception if they receive a warning and see flames and embers, as illustrated in Equation 5.

$Risk$ = 1 + (-0.487 x 0) + (-0.533 x 0) + (0. 738 x 1) + (0.927 x 1) + (0. 794 x 1) = 3.459 Equation 5

Given the perceived risk in Equation 5, it is then possible to calculate the probability that the individual will engage in a particular Behavioural States using the threshold in Table 3 and a logit link function (i.e., ordered logit formulation [51]):

1) Normal State: 1%;
2) Investigating State: 13%;
3) Vigilant State: 23%;
4) Response State: 63%.

Given the perceived risk of the *h* householder (R_h), which is calculated in Section 3.6, the probabilities (P_h) to be in Normal State ($S_h = 1$), Investigation State ($S_h = 2$), Vigilant State ($S_h = 3$), and Response State ($S_h = 3$) can be calculated assuming a logit link function (i.e., ordered logit formulation [51]) using Equations 6 and 7.

$$P_h\ (S_h = 1) = F(-0.936 - R_h)$$

$$P_h\ (S_h = 2) = F(1.606 - R_h) - F(-0.936 - R_h)$$

$$P_h\ (S_h = 3) = F(2.868 - R_h) - F(1.606 - R_h)$$ Equation 6

$$P_h\ (S_h = 4) = 1 - F(2.868 - R_h)$$

where *F* is defined as

$$F(x) = \frac{e^x}{(1 + e^x)}$$ Equation 7

3 Discussion

This paper provides a calibration solution for the Wildfire Decision Model (WDM) originally introduced in [1]. This is done using a Hybrid Choice Modelling (HCM) solution, which allows for the estimation of perceived risk (Risk) as a latent variable which then affects the behavioural state of householders. Depending on the value of Risk, the HCM is capable of identifying the likely behavioural state of the householders among Normal, Investigating, Vigilant and Response states. The calibration was run using the data collected for the 2016 Chimney Tops 2 wildfire.

The calibrated model in Table 2 shows that most of the regression weights are statistically significant and that the signs are in line with the existing literature summarized in Table 1; namely: warnings, fire cues, education, previous wildfire evacuation experience and time of residency in a property. The parameters weighting the impact of the distance of the wildfire, location, age, gender, and income are not statically significant, however. With regards to the lack of significance for the location and distance variables, this may be related to several uncertainties in the distance from the wildfire and household location variables. First, given privacy concerns, it was not possible to collect the exact location of the properties (instead, their census blocks were provided by the contractor). Also, the measurements for distance were recorded based on the final spread location of the wildfire, as real-time data of the wildfire front movement were not available. These assumptions may have resulted in considerable noise in these variables. In addition, the results did not show any impact of gender, age, or income on risk perception. However, these variables could correlate with many predictors that did affect the risk perception; namely, education, previous wildfire evacuation experience, and time of residency in a property. As a result, it is possible that these variables actually have an impact on risk perception, but the data did not provide enough heterogeneity among householders' factors to clearly measure it.

The utility modelling component of the HCM shows that risk perception is a good predictor to estimate the probability of householders' behavioural states. In fact, the model is capable of predicting more than 50% of the behavioural states of the data used in this study (i.e., a normal, investigative, vigilant, or responsive state; see cross-validation in Section 3.5.2), and more than 75% of a simple binary choice (react or not). The results also quantify for the first time that the risk thresholds introduced in [1] can identify householders' transition from one behavioural stage to another behavioural state, as illustrated in Figure 7.

Given the simplicity of the linear formulation of Equations 1, 2 and 3, it is possible to simply implement the proposed model to estimate the risk perceived by a householder based on his/her internal (i.e., education, previous wildfire evacuation experience, and time of residency in a property) and external (i.e., warning and fire cues) factors, when this data is available. This estimated risk can be then used to predict the probability of engagement in each behavioural

state (i.e., normal, investigative, vigilant, or responsive) for a selected household. This can be easily achieved using the close formulation of the ordered logit models described in [51]. As such, the proposed model has high potential to be implemented in many existing wildfire simulation frameworks [9], [11].

As limitations to this work, data used in this modeling effort was obtained from a specific population and fire event and may not be completely generalizable to other events. More specifically, our sample of residents from the Gatlinburg, TN area consisted of generally lower income and older individuals who were unexperienced with wildfires, which may not be reflective of other WUI populations or regions of the country where wildfires are a more common occurrence, or fuel loads and fire behavior differ. While the addition of an online sampling method was intended to reduce sampling bias present within a mail-only approach (e.g., by reaching individuals who may have moved away after the fire event) it is possible that some bias is still present (e.g., by reaching those who have access to the internet and are active on social media, or read local area papers). Our sample also did not include tourists and other nonresidents who may have experienced the event. As such, more wildfire evacuation data from different disasters and calibration efforts are required to verify and validate the generalizability of the proposed calibration solution. This can be achieved by using a similar questionnaire tool gather data from householder in a relatively similar geographic location and having similar demographics and previous experience who have been affected by a comparable wildfire event.

Another limitation of this work is that it does not account for the uncertainty of the external factors. For instance, given the existing wildfire data, it was not possible to investigate the impact of the progression of the wildfire over time as location- and time-specific information about the wildfire regarding Chimney Tops 2 wildfire are not available. Moreover, another source of uncertainty is related to the flow of information received through warnings that might affect the decision-making process. As such, future studies need to account for uncertainties by increasing the quality and resolution of the data related to external factors as well as by using stochastic or semi stochastic modelling to account these external uncertainties.

Finally, using post-disaster questionnaires can introduce another layer of uncertainty within the behavioral data as respondents were asked to remember events and actions taken several months after the wildfire disasters. As such, this might affect the accuracy of the information provided by householders. This issue can be mitigated in future studies by running questionnaire studies as soon as it is ethically possible after a wildfire event or by investigating evacuation behaviours by using other revealed preference techniques (i.e. observing household behaviour that is tracked by mobile devices such as smartphones) instead of questionnaires.

As a result, future work is necessary to provide further calibration of the WDM using new data from different wildfire events and locations. This can be achieved by continuing to collect data

using similar versions of the questionnaire described in Section 3.2. Even better, standardized data could be collected on evacuation decision-making across events if a standard surveyed were to be developed and adopted by researchers within the wildfire field. By collecting new data from different countries, it will also be possible to further investigate the impact of culture on householder behaviour during wildfire emergencies. Other future work is also necessary to investigate the impact of potential non-linearities using machine learning, as well as household heterogeneities using logit mixture. These relatively new techniques have already shown their potential for building more accurate fire evacuation models [52], [53].

4. Conclusion

The Wildfire Decision Model (WDM) originally introduced in [1] is fully calibrated in this work This using a Hybrid Choice Modelling (HCM) solution. The paper illustrates how HCM is a useful tool when investigating the decision-making process of householders using latent variables such as risk perception.

The calibrated model allows investigating how several external and internal factors affect householders' wildfire risk perception and behavioral states. The calibrated model highlights that receiving warnings and seeing wildfire flames and embers increased the risk perception and the likelihood to decide to start evacuating. Moreover, householders' educational level, length of residence in an area and previous evacuation experiences had impact on the risk perception. Future studies are needed to investigate other wildfire disasters affecting householders with different demographics as well as the decision-making of nonresidents who may have experienced these events.

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References:

[1] R. Lovreglio, E. D. Kuligowski, S. M. V. Gwynne, and K. Strahan, "A Modelling Framework for Householder Decision-Making for Wildfire Emergencies," *Int. J. Disaster Risk Reduct.*, 2019.

[2] G. Boustras, E. Ronchi, and G. Rein, "Fires: fund research for citizen safety," *Nature*, vol. 551, no. 7680, pp. 300–300, Nov. 2017.

[3] "Spreading like wildfire," *Nature Climate Change*, vol. 7, no. 11, Nature Publishing Group, p. 755, 01-Nov-2017.

[4] Y. Liu, J. Stanturf, and S. Goodrick, "Trends in global wildfire potential in a changing climate," *For. Ecol. Manage.*, vol. 259, no. 4, pp. 685–697, Feb. 2010.

[5] NRCAN, "Wildland fire evacuations," *https://www.nrcan.gc.ca/forests/climate-change/forest-change/17787*, 2019. .

[6] NIFC, "Wildland Fire Fatalities by Year," 2019.

[7] E. Ronchi, S. M. V. Gwynne, G. Rein, P. Intini, and R. Wadhwani, "An open multi-physics framework for modelling wildland-urban interface fire evacuations," *Saf. Sci.*, vol. 118, pp. 868–880, Oct. 2019.

[8] X. Zhao, R. Lovreglio, E. Kuligowski, and D. Nilsson, "Using Artificial Intelligence for Safe and Effective Wildfire Evacuations," *Fire Technology*. Springer, pp. 1–3, 15-Apr-2020.

[9] P. Intini, E. Ronchi, S. Gwynne, and A. Pel, "Traffic Modeling for Wildland-Urban Interface Fire Evacuation," 2019.

[10] E. Ronchi and S. Gwynne, "Computational Evacuation Modeling in Wildfires," in *Encyclopedia of Wildfires and Wildland-Urban Interface (WUI) Fires*, Springer International Publishing, 2019, pp. 1–10.

[11] E. Ronchi, G. Rein, S. Gwynne, R. Wadhwani, P. Intini, and A. Bergstedt, "e-Sanctuary: Open MultiPhysics Framework for Modelling Wildfire Urban Evacuation - Fire Protection Research Foundation," 2017.

[12] A. Beloglazov, M. Almashor, E. Abebe, J. Richter, and K. C. B. Steer, "Simulation of wildfire evacuation with dynamic factors and model composition," *Simul. Model. Pract. Theory*, vol. 60, pp. 144–159, Jan. 2016.

[13] T. J. Cova and J. P. Johnson, "Microsimulation of Neighborhood Evacuations in the Urban–Wildland Interface," *Environ. Plan. A*, vol. 34, no. 12, pp. 2211–2229, Dec. 2002.

[14] H.-S. Gan, K.-F. Richter, M. Shi, and S. Winter, "Integration of simulation and optimization for evacuation planning," *Simul. Model. Pract. Theory*, vol. 67, pp. 59–73, Sep. 2016.

[15] D. Li, T. J. Cova, and P. E. Dennison, "Setting Wildfire Evacuation Triggers by Coupling Fire and Traffic Simulation Models: A Spatiotemporal GIS Approach," *Fire Technol.*, pp. 1–26, Sep. 2018.

[16] B. Wolshon and E. Marchive, "Emergency Planning in the Urban-Wildland Interface: Subdivision-Level Analysis of Wildfire Evacuations," *J. Urban Plan. Dev.*, vol. 133, no. 1, pp. 73–81, Mar. 2007.

[17] L. H. Folk, E. D. Kuligowski, S. M. V. Gwynne, and J. A. Gales, "A Provisional Conceptual Model of Human Behavior in Response to Wildland-Urban Interface Fires," *Fire Technol.*, vol. 55, no. 5, pp. 1619–1647, Sep. 2019.

[18] J. McLennan, B. Ryan, C. Bearman, and K. Toh, "Should We Leave Now? Behavioral Factors in Evacuation Under Wildfire Threat," *Fire Technology*, vol. 55, no. 2. Springer

New York LLC, pp. 487–516, 15-Mar-2019.

[19] T. Toledo, I. Marom, E. Grimberg, and S. Bekhor, "Analysis of evacuation behavior in a wildfire event," *Int. J. Disaster Risk Reduct.*, vol. 31, pp. 1366–1373, Oct. 2018.

[20] K. W. Strahan, J. Whittaker, and J. Handmer, "Predicting self-evacuation in Australian bushfire," *Environ. Hazards*, pp. 1–27, Aug. 2018.

[21] S. Mccaffrey, R. Wilson, and A. Konar, "Should I Stay or Should I Go Now? Or Should I Wait and See? Influences on Wildfire Evacuation Decisions," *Risk Anal.*, vol. 38, no. 7, 2018.

[22] S. D. Wong, J. C. Broader, J. L. Walker, and S. A. Shaheen, "Understanding California Wildfire Evacuee Behaviorand Joint Choice-Making - Working Paper," 2020.

[23] M. Ben-Akiva *et al.*, "Hybrid Choice Models: Progress and Challenges," *Mark. Lett.*, vol. 13, no. 3, pp. 163–175, Aug. 2002.

[24] J. Walker and M. Ben-Akiva, "Generalized random utility model," *Math. Soc. Sci.*, vol. 43, no. 3, pp. 303–343, 2002.

[25] D. Bolduc and R. Alvarez-Daziano, "On Estimation of Hybrid Choice Models," in *Choice Modelling: The State-of-the-art and The State-of-practice*, Emerald Group Publishing Limited, 2010, pp. 259–287.

[26] M. K. Lindell and R. W. Perry, *Communicating Environmental Risk in Multiethnic Communities*. 2004.

[27] P. A. Reneke, "Evacuation Decision Model," 2013.

[28] R. Lovreglio, E. Ronchi, and D. Nilsson, "A model of the decision-making process during pre-evacuation," *Fire Saf. J.*, vol. 78, 2015.

[29] R. Lovreglio, E. Ronchi, and D. Nilsson, "An Evacuation Decision Model based on perceived risk, social influence and behavioural uncertainty," *Simul. Model. Pract. Theory*, vol. 66, no. April, pp. 226–242, Aug. 2016.

[30] I. M. McNeill, P. D. Dunlop, T. C. Skinner, and D. L. Morrison, "Predicting delay in residents' decisions on defending v. evacuating through antecedents of decision avoidance," *Int. J. Wildl. Fire*, vol. 24, no. 2, pp. 153–161, Apr. 2015.

[31] E. Ronchi, P. A. Reneke, and R. D. Peacock, "A Method for the Analysis of Behavioural Uncertainty in Evacuation Modelling," *Fire Technol.*, Jul. 2013.

[32] R. Lovreglio, E. Ronchi, and D. Borri, "The validation of evacuation simulation models through the analysis of behavioural uncertainty," *Reliab. Eng. Syst. Saf.*, vol. 131, pp. 66–174, 2014.

[33] P. Mozumder, N. Raheem, J. Talberth, and R. P. Berrens, "Investigating intended evacuation from wildfires in the wildland–urban interface: Application of a bivariate probit model," *For. Policy Econ.*, vol. 10, no. 6, pp. 415–423, Aug. 2008.

[34] T. B. Paveglio, T. Prato, D. Dalenberg, and T. J. Venn, "Understanding evacuation preferences and wildfire mitigations among northwest Montana residents," *Int. J. Wildl. Fire*, vol. 23, pp. 435–444, 2014.

[35] R. Alsnih, J. Rose, and P. Stopher, "Understanding household evacuation decisions using a stated choice survey: case study of bush fires," in *Transportation Research Board Annual Meeting, 84th*, 2005.

[36] J. McLennan, S. Cowlishaw, D. Paton, R. Beatson, and G. Elliott, "Predictors of south-eastern Australian householders' strengths of intentions to self-evacuate if a wildfire

threatens: two theoretical models," *Int. J. Wildl. Fire*, vol. 23, no. 8, p. 1176, Dec. 2014.

[37] J. McLennan, G. Elliott, and M. Omodei, "Householder decision-making under imminent wildfire threat: stay and defend or leave?," *Int. J. Wildl. Fire*, vol. 21, no. 7, p. 915, 2012.

[38] J. McLennan, G. Elliott, M. Omodei, and J. Whittaker, "Householders' safety-related decisions, plans, actions and outcomes during the 7 February 2009 Victorian (Australia) wildfires," *Fire Saf. J.*, vol. 61, pp. 175–184, Oct. 2013.

[39] C. C. Benight, "Collective efficacy following a series of natural disasters," *Anxiety, Stress Coping*, vol. 17, no. 4, pp. 401–420, Dec. 2004.

[40] L. Strawderman, A. Salehi, K. Babski-Reeves, T. Thornton-Neaves, and A. Cosby, "Reverse 911 as a Complementary Evacuation Warning System," *Nat. Hazards Rev.*, vol. 13, no. 1, pp. 65–73, Feb. 2012.

[41] J. Whittaker and J. Handmer, "Community bushfire safety: a review of post-Black Saturday research," *Aust. J. Emerg. Manag.*, vol. 35, no. 4, 2010.

[42] V. H. Guthrie, M. J. Finucane, P. E. Keith, and D. B. Stinnett, "After Action Review of the November 28, 2016, Firestorm - ABS Group," 2017.

[43] National Park Service, "Chimney Tops 2 Fire Review -Individual Fire Review Report," 2017.

[44] J. Sorensen, B. Sorensen, A. Smith, and Z. Williams, "Results of An Investigation of the Effectiveness of Using Reverse Telephone Emergency Warning Systems in the October 2007 San Diego Wildfires," 2009.

[45] J. McLennan and G. Elliott, "Wait and see': the elephant in community bushfire safety room," in *the Bushfire CRC & AFAC 2012 conference research forum*, 2012, pp. 56–69.

[46] J. H. Sorensen, D. S. Mileti, and J. T. Needham, "Warnings and Human Response in the Oroville Dam Crisis, February 2017," *AGUFM*, vol. 2017, pp. PA23D-02, 2017.

[47] G. Brown, "Factor Analysis: A course using Jamovi & lavaan," *Collection*, 2019.

[48] D. Hooper, J. Coughlan, and M. Mullen, "Structural Equation Modelling: Guidelines for Determining Model Fit," *Articles*, Jan. 2008.

[49] L. T. Hu and P. M. Bentler, "Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives," *Struct. Equ. Model.*, vol. 6, no. 1, pp. 1–55, 1999.

[50] B. M. Byrne, *Structural equation modeling with Mplus : basic concepts, applications, and programming*. Routledge Academic, 2012.

[51] W. H. Greene and D. A. Hensher, *Modeling Ordered Choices: A Primer*. Cambridge University Press, 2010.

[52] X. Zhao, R. Lovreglio, and D. Nilsson, "Modelling and Interpreting Pre-Evacuation Decision-Making Using Machine Learning," *Autom. Constr.*, 2020.

[53] X. Song and R. Lovreglio, "Investigating Personalized Exit Choice Behavior in Fire Accidents Using the Hierarchical Bayes Estimator of the Random Coefficient Logit Model," *Anal. Methods Accid. Res.*, 2020.

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Lovreglio R

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