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# Theoretical frameworks of risk perception and protective behaviour: an empirical comparison

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## Abstract

Climate change and socio-economic development in disaster-prone areas are causing rising risks over time, especially flooding, which is a worsening global issue. Flood risk management requires proactive action by all the stakeholders, including those residing in flood-prone areas, and understanding how these humans perceive flood risk and adapt is crucial for effective disaster risk management policy. However, there is a high degree of heterogeneity in how researchers from the different disciplines involved have approached this field, including social vulnerability. While this has resulted in a range of competing theories that have been operationalised, they are usually implemented in different studies instead of empirically compared. This paper addresses this gap by comparing the power of the six main behavioural theories (Expected Utility Theory; Protection Motivation Theory; Protective Action Decision Model; Social Capital Theory; Hazards-of-Place; and Cultural Theory of Risk). We explore the extent to which the theories explain risk perceptions relative to one another; the extent to which they explain adaptive behaviour compared to each other; and better than others. We conduct this analysis using a sample of 5,000 Paris metropolitan residents surveyed in 2022. Our analysis finds that the Protective Action Decision Model (PADM) and the Hazards-of-Place (HoP) inspired models describe the largest amount of observed variability. While no theory was very effective at predicting specific emergency behaviours, they are often overlooked in the literature. Moreover, rationalist and constructivist approaches could be combined to refine the theories, as both models are suitable for being nested together in future research.

**Keywords** Risk perception · Adaptation · Disaster risk reduction · Flood · Protective action decision model · Hazards-of-place

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## 1 Introduction

Flooding is a worsening global issue. Swiss Re reports that globally flooding caused US\$286bn of reported monetary damage over 2018–2022, which is a nearly 40% increase compared to 2013–2017 (Swiss Re, 2023). Individual flood events can also be devastating as the 2021 flood across Europe had a UD\$54bn monetary loss (Munich Re, 2022) while the 2022 Pakistan flood had a monetary loss of US\$15bn and over 1700 fatalities (Munich Re, 2023). Flood events are expected, overall, to become increasingly impactful due to a combination of changes in climate hazard, exposure, and vulnerability (IPCC 2022).

In this paper, we focus upon two of these three elements in the form of exposure (i.e., what can be damaged during a flood) and vulnerability (i.e., how susceptible things are to be damaged) as these are directly related to human decision making. For instance, property owners can implement a range of flood risk management strategies that can help them manage or limit the impacts of flooding, collectively known as property-level flood resilience (PLFR) strategies, which are known to be effective (Lamond et al. 2018; Poussin et al. 2015; Kreibich et al. 2015; Hudson et al. 2014, 2019). Therefore, the actions of property-owners and residents with flood-prone areas has become of great interest as part of integrated flood risk management strategies (Aerts et al., 2018; Thieken et al., 2016; Bubeck et al. 2016). However, given the nature of PLFR the implementation of such strategies is often voluntary and implementation, is therefore, dependent on individual behaviour.

This dependency on individual behaviour has led to a great deal of research into the behavioural underpinnings of people's behaviour within flood risk management to understand the levers that be pushed to create a more flood resilient society (Kuhlicke et al. 2020; Priest 2021). Kuhlicke et al. (2023) show that this is a very divergent field with many behavioural theories potentially being applicable to different aspects of this problem depending on what aspect of behaviour is being focused upon or the hypothesised process that the creator sought to model. Therefore, not only could different behavioural theories explain the variation in observed behaviour to different extents, but they can produce frameworks that are not necessarily compatible or directly comparable with each other. Moreover, the same theory can be operationalised differently by different researchers, in part due to the need to adapt survey questions to research goals and local needs. This leads to a large degree of epistemological uncertainty, that in turn limits overall generalizability and comparability (Lechowska 2022; Staupe-Delgado et al. 2022). Therefore, it is difficult to draw systematic conclusions on the reliability or accuracy of different behavioural theories to predict behaviour (Rufat et al. 2022).

In this paper, we seek to address part of this gap by conducting a systematic comparative analysis of the explanatory power of six different behavioural theories, via a theory driven modelling approach, using a survey designed to map multiple different behavioural theories. This survey was conducted in Paris in 2022 and focused upon investigating risk perceptions, preparedness, and experiences of the 2016 and 2018 Parisian floods. Using this data, we explore which of the six studied behavioural theories explains the most variation in risk perceptions and adaptive behaviour relative to one another and if improved results can be gathered by linking different aspects of the behaviour theories together rather than using the behavioural theories independently.

## 2 Theories investigated

The process of understanding behavioural response to natural hazards, while arguably having no singular law of human behaviour (Loucks 2015) can be separated into constructivist and rationalist perspectives (Lechowska 2022).

The constructivist perspective places a primary focus on the social construction of risk, asserting that perceptions and behaviour are shaped by shared social, cultural, and political factors (Birkholz et al. 2014). Therefore, the constructivist approach highlights the absence of a universal understanding of behaviour (Lechowska 2018), rather behaviour is a contextual phenomenon driven by socio-cultural factors (Birkholtz et al., 2014). In contrast, the rationalist perspective emphasizes the analysis and construction of threats as a key element of decision-making based on available information, probabilities, and potential consequences. The decision-making process is perceived as logical reasoning that result in an outcome that the individual views as subjectively the best for them (Birkholz et al. 2014). The rationalist perspective suggests that there are principles governing behaviour across social contexts (Lechowska 2022).

Out of the existing theories, we pick six theories that cover various aspects of the range of possible behavioural drivers based on the prominence in which they are employed in the scientific literature, as presented in Kuhlicke et al. (2023), that also can be split across the constructivist and rationalist paradigms. However, while the theories presented below are presented as belonging to one of these two paradigms there is the potential for the theories to form a spectrum between unflexible universal rules and flexible contextually defined norms (e.g., compare the Expected Utility Theory and the Cultural Theory of Risk). Therefore, the allocation of theories to a specific paradigm is based on which paradigm the theory mostly falls into.

Additionally, it should be noted that our intended purpose is to use these theories to build empirical models and explore their relative ability to explain the variation observed or self-stated behaviour and risk perception and to a lesser extent how they conform to the expected results suggested by the underpinning theory, rather than to provide detailed empirical insights into the behaviour of Parisians. Moreover, while all 6 theories have been used to explain risk perceptions and adaptive behaviour it must be caveated that this is not necessarily how they theory was originally intended but matches how it has been used. For example, HoP may not be directly intended as a behavioural model but it has been used to explain differences in behaviour implicitly moving the HoP approach into the behavioural space.

### 2.1 Rationalist

#### 2.1.1 Expected utility theory (EUT)

Expected utility theory is a principal component of neoclassical economics concerning how people make decisions under uncertainty. Expected utility theory as developed by von Neumann and Morgenstern (1947) posits that to undertake a protective action an individual will assess the utility of the outcome with the protective action in place to the situation without the action, where a positive difference will result in the behaviour being implemented. However, in practice direct monetary values are used as a simplification for measuring utility. The original expected utility theory supposed that individuals knew the

objective probability of negative events occurring, while there are extensions such as Savage (1954)'s subjective utility theory that supposes that are utility functions and perceived probability distributions that are individual specific. It should also be noted that EUT was designed as a stylised modelling tool (Schoemaker, 1982) rather than as a behavioural theory, for which it has been long criticized (Tversky 1975).

### 2.1.2 Protection motivation theory (PMT)

Protection Motivation Theory (PMT) is a psychological framework originally proposed by Rogers (1975) and Rogers (1983) within the health field but has since been widely employed (Grothmann and Patt 2005). PMT, as a psychological model, places its focus on the mental process of the individual. Originally, PMT proposes that an individual's degree of threat appraisal and coping appraisal and their interaction explains a person's protective behaviour. Threat Appraisal aligns with risk perceptions (i.e., the person acknowledges that there is a threat) and is comprised of the perceived severity or consequences of a potential threat and the perceived probability of the threat occurring. The coping appraisal element of PMT is the subjective assessment of how well and effective a person thinks the actions that they can take against the threat are. Coping appraisal can in turn be sub-divided into self-efficacy (i.e., the individual's belief in their ability to perform protective behaviours), Response-efficacy (i.e., the individual's belief that the available protective actions can and will offer protection against the threat), and response-cost (i.e., the individual's perception that the protective measures are not too costly in terms of resources or effort).

The overall level of protection motivation is determined by the balance between the perceived threat appraisal and the perceived coping appraisal. An individual with a high perceived threat and coping appraisal is deemed to be more likely to engage in protective behaviours. A further consideration is the role of "maladaptive" thinking or outcomes. Maladaptive outcomes occur within PMT as a combination of high threat appraisal and low coping appraisal leading to a psychological coping response that aids the mental well-being of the individual but not limit the threat (Dillenardt et al. 2022).

### 2.1.3 Protective action decision model (PADM)

Lindell and Perry (2012) present the Protective Action Decision Model (PADM) as a model that integrates a typology of social, environmental, and psychological cues to act. Lindell and Perry (2012) define three pre-decision processes for PADM that underpin the need to act as attention (i.e. a cue to kickstart the thinking process), exposure (i.e., a source of information), and comprehensions (i.e., the person's ability to understand and act upon the information). This then leads to the formation of three core perceptions—threat perceptions, protective action perceptions, and stakeholder perceptions—that generate the potential for a protective action once situational facilitators and impediments to action are considered. The PADM has been used in studies such as, e.g., Dillenardt et al. (2022), Liddell et al. (2020), and Strahan and Watson (2019).

Within the PADM model, the supposed sequential process of decision-making starts with a respondent being exposed to a series of environmental cues (e.g., observing heavy rain leading to a pluvial flood), social cues (e.g., seeing neighbours start to deploy mobile flood barriers or evacuating) and warnings (e.g. an official flood warning) (Lindell and Perry 2012). These cues represent informational channels that help inform behaviour, with the resulting behavioural impact being dependent on the traits of the individuals (e.g., if the

warning is in the recipient's first or second language, social embeddedness of the individual, financial resources etc.). These are the initial factors within a series of pre-decisional processes that generate the core perceptions of threat and protective actions. These perceptions provide the basis for decision making when considered with different situational framing factors that provided external context and constraints to a person's ability to act.

## 2.2 Constructivist

### 2.2.1 Hazards-of-place (HoP)

The hazards-of-place model (Cutter 1996; Cutter et al. 2012) suggests that individuals' understanding of and responses to disaster risks are influenced by the specific characteristics and hazard potentials associated with the places they inhabit and how society interacts with each other and nature. The HoP integrates exposure and social vulnerability, hence the multidimensional socio-economic and demographic character of a place or individual underscoring their local context (Cutter et al. 2013). However, it can be noted that this theory doesn't account for the root causes of social vulnerability, larger scale contexts, and post-disaster impact and recovery (Cutter et al. 2008).

### 2.2.2 Social capital theory (SCT)

Bourdieu (1986) presents social capital as the strength of the relationships an individual has that can be leveraged to achieved a certain goal or influence activity. Similarly, Putnam (2000) argues that social capital occurs through trust, norms, and networks that facilitate action. In this vein, Pelling and High (2005) separate social capital into three categories: bonding, bridging, and linking. Bonding social capital represents the relationships between individuals with a similar social identity; bridging capital captures the social relationships between those with contrasting social identities; linking social capital concerns the social relationships across individuals with differing power hierarchies. Therefore overall, social capital can be seen as well tightly embedded an individual is within and across specific groups in society.

In a social capital driven framework, social capital acts as an informal social institution which trigger protective actions because it can be seen as the as the expectation of regular, honest, and cooperative behaviour and support (Pelling and High 2005). Within this social context, the cultural institutions favoured by the cultural theory of risk are captured by the concept of "social norms" which are the unwritten social rules that guide behaviour within a specific social context and thereby acting as an informal social institution (Ostrom 2009). The informal social institutions formed by social norms and accessed through a "stock" of social capital represents the degree of support people may expect (or receive in practice) to receive during a disaster event or in their pre-event preparation, see e.g., Abunywah et al. (2023). However, Babicky and Seebauer (2017) and Hudson et al. (2020b) also present social capital as an avenue through which risk perceptions can be altered. This is because social capital represents how tightly connected a person is into different social groups that they see as relevant to them. Therefore, this can act as a pathway for transmitting vicarious experiences across groups- (i.e., experiences not directly impacting the individual but one for which they are empathetic) or social norms (e.g., no one in their perceived peer groups is adapting which changes their perception on the need to take action).

### 2.2.3 Cultural theory of risk (CTR)

The Cultural Theory of Risk, as developed in Douglas (1978) and Douglas and Wildavsky (1983) explores how different cultural contexts alter how people perceive and respond to risk due to their worldview. In this theoretical framework there is a spectrum of four major cultural biases that influence how individuals and societies perceive and respond to risk due to social institutions that are created (Steg and Sievers 2000; Birkholz et al. 2014; Thompson 2018; Dryzek 2022). Hierarchical cultures are characterized by a strong emphasis on social order, authority, and tradition. This translates into centralized control and regulations. Individualistic cultures emphasize personal autonomy, freedom, and individual responsibility. This translate into individuals being responsible for action. Egalitarian cultures value equality, community, and social justice. This translates into participatory decision-making and a suspicion of hierarchical structures. Fatalistic cultures are characterized by a sense of fatalism and a belief that events are largely beyond human control. This translates into a view of natural hazard risk as inevitable and unavoidable.

These cultural biases shape how individuals and societies perceive and respond to various risks due to their resulting social norms (Shaw et al. 2004). For example, Hudson et al. (2020a) discusses how different focuses on individualistic or egalitarian outcomes have led to divergences in how extreme weather insurance systems across Europe have been designed. Gould et al. (2016) show how the Chilian response to the 2010 earthquake moved in different directions as these biases altered in prominence. Therefore, the cultural theory of risk places the socio-cultural context, and the world view it engenders, in which an actor finds themselves, as the driver of risk perception and action due to the influence of what is seen as socially acceptable or valued understandings of risk and justify action (Douglas and Wildavsky 1983; Steg and Sievers 2000; Ridolfi et al. 2020).

## 3 Methodology

### 3.1 Data

The survey was administered face-to-face in the Paris metropolitan area (population of ~ 13 million) where more than one million residents are directly threatened by flooding and up to 5 million being indirectly threatened by flooding. Two flood events in 2016 and 2018 and one major European flood exercise in 2016 occurred in rapid succession, requiring large-scale evacuations (Rufat et al. 2024). The surveys were conducted from September to December 2022, after these flood events, and asked respondents to recall their actions during a flood or to speculate on their future intentions during a flood.

The survey provided a sample of 5000 responses. Respondents were randomly selected following a stratified random sampling technique, using both geographically based strata and social strata. This produced a sample that was representative at different spatial scales (municipality, county, metropolitan region) and different flood exposure levels across the Paris metropolitan areas. About half of the sample comprised residents living in the official 100-year floodplain. One-third were living in indirect impact zones, indicating that even if their home was not directly flooded, they could still face power, water, heating, or phone outages, and sewer backflows. The rest of the respondents lived outside of these exposure zones. The participants were randomly recruited until the location-specific age, gender and

education quotas were fulfilled for each location within the Paris metropolitan area. This sampling approach was critical to assess the possible discrepancies between the actual and perceived flood exposure.

### 3.2 Statistical approach

For each theory, we constructed one reference model with the specific combination of explanatory variables representing all its constructs (a summary table can be found in the Appendix). Once this reference model was created, a suitable dependent variable was selected which determined the nature of the regression model, five to seven dependent variables according to the theory. This resulted in 36 models. We then introduced five more models combining all the constructs from all theories for each dependent variable. We subsequently adjusted the models on samples ranging from 3094 to 4500 respondents, after setting aside 500 respondents (selected at random to subsequently assess the models predictive power).

The resulting 41 models measure the degree of information specific to each explanatory variable and the overall adjustment to the variation in peoples declared perceptions and intended behaviour. Dichotomous variables are modelled using logit logistic regressions. Polytomous variables are modelled using multinomial logistic regressions that measure the relative probability of each category. To the global  $p$ -value from likelihood-ratio tests is a statistic based on the difference between the likelihood-ratios of the model that includes all variables derived from a specific theory and the model under the null hypothesis without a specific explanatory variable. Using this information, we fitted the predictive models on the explanatory variables retaining a significant effect ( $p$ -value < 0.05). The pseudo- $R^2$  is a measure for goodness of fit, we used the adjustment proposed by Nico Nagelkerke to ensure that the maximum theoretical value is equal to one (perfect fit). For each theory, we consider the number and nature of the constructs that retain explanatory power for each dependent variable. Subsequently, we compared the predictive performance of these adjusted models, only retaining models with pseudo- $R^2$  greater than 0.2, on the test sample of the randomly set aside 500 respondents.

Our approach aims to assess the overall theory performance as well as the relevance of the constructs combination from each theory. For each reference model, we used the likelihood-ratio test to select the combination of constructs maximizing their pseudo- $R^2$ . Then, we ran those adjusted models (i.e., without the non-significant variables) on the 500 respondents test sample and measured their predictive power using Cohen's kappa. Kappa is a statistic quantifying the proportion of agreement between observed and predicted categories (Cohen 1960). The statistic considers both the true positive rate and the false positive rate, providing a balanced assessment of the model's performance. It ranges from 0 to 1, with 1 indicating perfect agreement between the predictions of the model and measured categories. In addition, we reported the  $p$ -value of a test comparing the proportion of correct predictions over the total number of cases (accuracy) to the accuracy that could be obtained if the model assigned all respondents either at random or to the more common (majority) category (null information rate) (Bicego and Mensi 2023).

The variables in Table 1 are used as the independent variables in these models to explore a range of different variables that the six behavioural theories could be used to explain. This range of variables was selected so that we can place the largest emphasis on adaptive behaviour as the questions allow us to cover stated behavioural intentions during the flood as a way of proxying their emergency behaviour (which is a neglected area of research in

**Table 1** Dependent variables description

Variable Name	Description
Risk perception: Relative exposure	<i>Is your home more, or less, exposed to flooding than the rest of the Paris region?</i> much less, less, more, much more
Risk perception: Perceived probabilities*	<i>In your neighbourhood, how often does flooding occur?</i> every year, 5 years, 10, 30, 50, 100+, never
Risk perception: Perceived impact*	<i>In your neighbourhood, can floods have serious consequences?</i> very serious, serious, not really serious, not serious at all
Emergency behaviour: get car	<i>In case of flooding, would you go and get your car from the street?</i> Yes, no
Emergency behaviour: score	A total value corresponding to the number of “yes” answers to the following: - <i>In case of flooding, would you go and get your car from the street?</i> - <i>In case of flooding, would you go to the cellar, underground parking, or basement?</i> - <i>In case of flooding, would you use a personal generator in case of a power cut?</i> - <i>To save time, would you use the routes closed due to flooding by car, bike, foot?</i>
Adaptation: Structural adaptation	<i>Is your home flood proof or adapted to floods?</i> Yes, no
Adaptation: score	A total value corresponding to the number of “yes” answers to the following: - <i>Have you done any work or adaptations to make your home flood proof?</i> - <i>Did these flood experiences cause you to change accommodation (move out), home improvements (ventilation, rooms), preparations (more stocks)?</i> - <i>Did the experiences of the pandemic and the lockdowns cause you to change accommodation (move out), home improvements (flood proofing, electricity, rooms), preparations (more stocks)?</i>

Variables noted with an \*could not be used in the rationalist theories as they form part of the explanation for adaptive behaviour and as such become independent variables

the behavioural drivers of flood risk adaptation) as well as their behaviour pre/post flood with wider building level precautionary measures. The risk perception category of variables is included as these are relevant dependent variables for the constructivist theories to explain and form important explanatory variables for rationalist theories.

The independent variables for each of the six behavioural theories are presented in the following sub-sections. While all the questions can be taken from the same survey and are therefore operationalised in the same way across each behavioural theory, we take theory-driven modelling approach to selecting the independent variables for each behavioural theory. This means that variables were selected based on how closely and completely they aligned with a given behavioural theory. A full list of the variables and their description can be found in the Appendix. In these variables the “don’t know” answers were included as a separate response category to retain as large a sample as possible. Moreover, excluding the respondents who express “don’t know” can result in the introduction of a sample

selection bias as discussed in Rufat and Botzen (2022). These responses act as the baseline comparison group where relevant.

### 3.2.1 Expected utility theory (EUT) operationalisation

For EUT our process of operationalisation begins with an understanding that we do not have a preexisting utility function that we can decompose into calculations of utility pre- and post-employment of protective measures. Therefore, we seek to proxy the features of the (subjective) expected utility decision-making process through the survey questions that capture these features. The essential features to proxy would be the expected impact of a flood (capturing elements of the size of the problem), risk aversion, and their perceived ability to limit the impacts of a possible flood (capturing an element of the perceived “cost” of implementing a potential solution) due to the absence of detailed data on the effectiveness of protective measures.

With this limitation in mind, we have elected to suppose that the process will be, primary, driven by the respondent’s perceived damage and ease at which they believe they can prevent it. We have taken this approach to model EUT based on the concept of opportunity cost. One way of understanding the role of the opportunity cost in decision-making is that we compare the action that we are considering to the best alternative. For example, employing a protective measure nor not. From this starting point, we can assume that there is a heterogeneous level of flood concern across the population, but that increasing potential flood impacts represent a negative utility if experienced. Therefore, the larger the perceived impact, or lower perceived cost of acting, it is more likely that a person’s opportunity cost of not acting becomes increasingly less attractive and, as such, less likely to be the optimal choice of the respondent.

Following this approach, we attempt to model as parsimony as possible this aspect of the EUT decision. We do this by modelling the expected impact (i.e., probability of impact\*magnitude of impact) through the respondent knowing they were in a flood-zone (perceived direct exposure), their expected probability of being flooded (probabilities), their expected impact if they were flooded (consequences), the expected ability to control flood impacts (self-efficacy), their expected payoffs, as well as a proxy for their risk aversion. A proxy for risk aversion is included because standard expected utility theory assumes that people are risk averse, which means that they are willing to pay more to prevent a negative random impact (e.g., a flood) impacting utility. Therefore, we would expect that a higher relative level of risk aversion would increase the perceived opportunity cost of not employing protective behaviours.

### 3.2.2 Protection motivation theory (PMT) operationalisation

PMT, at its most parsimonious, consists of threat appraisal (expected probability and expected impact) and coping appraisal. Coping appraisal consists of three sub-elements: Self-efficacy (i.e., I can successfully implement a protective action); Response-efficacy (i.e., the protective actions I can implement are effective); and response-cost (i.e., that the measure is not too burdensome). Threat appraisal is captured via perceived exposure (direct and indirect), perceived probability, costs and impacts. Coping appraisal is more complex to model but is captured via self-efficacy and response-efficacy. We would argue that perceived preparedness acts as a proxy measurement for response-efficacy because the more prepared the respondent believes their household should be correlated with the degree to

which they believe that these measures to be successfully reducing potential flood impacts. Moreover, for this reason it also potentially captures part of self-efficacy as well because similarly a person who is well prepared should perceive themselves to have a higher level of self-efficacy post-implementation because they have successfully implemented what they consider to be protective actions.

While we cannot actively model response-costs from the questions asked in the survey, an argument can be made for self-efficacy and response-efficacy being the most significant factors of coping appraisal to be modelled (Bubeck et al., 2018). Moreover, we employ a further common extension of PMT which is previous flood experience (we implement both direct and indirect experience). Previous flood experience is included because it is acknowledged that there are wider behavioural heuristics associated with low-probability/high-impact events such as flooding can have very different adaptation pathways based on if a person has experienced a flood or not. This is because the subjective psychological impacts of flooding can be long-lasting (Bubeck et al. 2020), which implies a long-lasting alteration of people's decision-making process (unlike the forward looking marginal decision-making process implied by EUT).

### 3.2.3 Protective action decision model (PADM) operationalisation

It can be argued that the core factors of PMT are considered within PADM's concepts of threat perceptions and protective action perceptions, which are then embedded within the socio-environmental content a person finds themselves within. Therefore, PADM builds upon PMT by including a wider series of steps in informational nodes in the decision-making process. Therefore, we begin this study's operationalisation through using the same variables as described in the previous section, on the assumption that this captures the same core tenants.

PADM conceptually expands upon the core elements of PMT with segments regarding information seeking and a series of framing factors. We proxy the information seeking behaviour of respondents with the respondent's reported behaviour on if they remember receiving information from previous flood risk events or information campaigns as well as seeking official government information. The more complex component is that of the framing factors, which represent a series of relevant contextual factors that could be expected to explain a person's behaviour in a way that also maintains a distinct perspective from the other behavioural theories used in the current study. Therefore, we expand the core elements of PADM with framing factors that consist of the degree to which respondents worry about flooding, the degree to which a person believes that the responsibility to act against flooding belong to them and previous experience with indirect flood impacts such as power cuts.

### 3.2.4 Hazards-of-place (HoP) operationalisation

The HoP model has not been implemented to explain risk perception to the best of our knowledge (Drakes and Tate 2022). While a handful of studies have explored the relationships between social vulnerability, risk perception (Armas et al. 2015; Adelekan and Asinyanbi 2016) and/or adaptive behaviour (Grothmann and Reusswig 2006; Olofsson and Öhman 2015), the vast majority settles for a few isolated demographic indicators, e.g. age, gender, education, (Wachinger et al. 2013; Lechowska 2018) or conflate vulnerability with hazard exposure (Tanner and Árvai 2018). More systematic studies have suggested that vulnerable groups could be more uncertain about risks, have insufficient knowledge, and end-up

being misrepresented in risk perception studies (Rufat and Botzen 2022; Noll et al. 2023). Whilst there is no definitive list of variables to implement the HoP model, there is despite the model's flexibility convergence in the variables used to derive composite indices of social vulnerability (Burton et al. 2018). In our study, the explanatory variable selection is derived from that convergence, ensuring a good representation of the HoP model as proxied via the respondents socio-demographic profile, exposure and past flood experiences.

### 3.2.5 Social capital theory (SCT) operationalisation

While a very limited number of studies have explored the relationships between social capital and risk perception (Lo and Cheung 2016; Babczyk and Seebauer 2017; Hudson et al. 2020a, b), the SCT is seldom explicitly mentioned (Kuhlicke et al. 2023). In addition to the linking dimension of the SCT represented in previous studies by social capital's degree of social interconnectedness, we include proxies of social norms and responsibility to account for the bonding aspect of social capital (Pelling and High 2005) following the logic that these represent how closely connected to their community they feel. We additionally control for social vulnerability drivers to represent the bridging dimension (Ómarsdóttir et al. 2022). As a result of the inclusion of social vulnerability variables, our study might offer an optimistic expansion of the explanatory power of the SCT. This is however the most comprehensive implementation of the theory to explain risk perception and adaptive behaviour.

### 3.2.6 Cultural theory of risk (CTR) operationalisation

CTR has mainly been used inductively to interpret empirical observations on disaster response driven by the risk perception of different groups (Scolobig et al. 2012; Snel et al. 2019). It has been argued that CTR can hardly be measured in surveys (Rippl 2002), or that the scales lack reliability (Rufat 2015), which might explain why empirical support for this theory has been surprisingly meagre (Johnson and Swedlow 2020). Following Swedlow et al. (2020), we have combined two items answered on 5-point scales for each of the four CTR worldviews (hierarchical, individualistic, egalitarian, fatalistic) with scores on trust and scales on subjective norms. While robust instruments of CTR measurement are still lacking and deductively derived survey measures have been found to exhibit much better model fit in factor analysis than in regression models (Johnson and Swedlow 2023), reusing some answers on 5-point scales for each worldview is the best approximation of CTR that we could implement in the same survey as the other theories.

## 4 Results

The objective of this paper is to explore to what extent the different theories explain the observed variation in the selected dependent variables as compared to one another. Therefore, the discussion and results presented below focus on the relative outcomes for the models inspired by each theory in terms of the statistical significance of the independent variables,<sup>1</sup> the model fit criteria (pseudo  $R^2$ ), and then their predictive performance (kappa).

<sup>1</sup> While the coefficients and their directionality are mentioned in the text where relevant, the coefficients can be found in the supplementary information.

**Table 2** Expected utility theory results (EUT)

	Exposure	Emergency behaviour	Emergency behaviour score	Adaptation	Adaptation score
probabilities	***	—	—	***	***
consequences	***	* (-)	* (-)	***	***
payoffs	—	** (-)	** (-)	—	*** (-)
self-efficacy	***	—	***	***	***
risk aversion	—	* (-)	***	—	** (-)
model	Multinomial	Binomial	Multinomial	Binomial	Multinomial
pseudo R <sup>2</sup>	0.38	0.03	0.08	0.28	0.36
N	3462	4500	4500	4500	4500

The following symbols represent the respective levels of statistical significant: — n.s., \* 5%, \*\* 1%, \*\*\* 0.1%

(-) Indicates that the only significant effect is answering “I don’t know” as opposed to the other answers to the question

**Table 3** Protection motivation theory results (PMT)

	Exposure	Emergency behaviour	Emergency behaviour score	Adaptation	Adaptation score
Perceived expo-sure (direct)	***	—	* (-)	**	**
Perceived expo-sure (indirect)	*	—	* (-)	*	***
Previous exp-erience (direct)	***	*** (-)	*	***	***
Probabilities	***	—	—	***	***
Consequences	***	—	—	**	—
Cost appraisal	—	** (-)	** (-)	—	** (-)
Self-efficacy	***	—	***	***	***
Response-efficacy	**	—	***	***	***
Model	Multinomial	Binomial	Multinomial	Binomial	Multinomial
Pseudo R <sup>2</sup>	0.44	0.03	0.08	0.33	0.48
N	3462	4500	4500	4500	4500

The following symbols represent the respective levels of statistical significant: — n.s., \* 5%, \*\* 1%, \*\*\* 0.1%

(-) Indicates that the only significant effect is answering “I don’t know” as opposed to the other answers to the question

#### 4.1 Rationalist theory results

For the three rationalist theories, we see that the EUT inspired model (Table 2) has a good adjustment (pseudo R<sup>2</sup> of 0.38) for risk perception (relative flood exposure) despite not controlling for actual exposure, as it is overlooked by the theory: only the risk aversion and payoffs proxies are not significant. The PMT inspired model (Table 3) has a

**Table 4** Protection action decision model results (PADM)

	Exposure	Emergency behaviour	Emergency behaviour score	Adaptation	Adaptation score
Perceived exposure (direct)	***	—	—	**	*
Perceived exposure (indirect)	—	—	—	—	**
Previous experience (direct)	—	* (–)	—	***	***
Previous experience (indirect)	***	***	* (–)	***	***
Worry	***	** –	—	—	*
Threat	—	—	—	—	—
Probabilities	***	—	—	***	**
Consequences	***	—	—	—	—
Control	***	—	—	—	—
Cost appraisal	—	** (–)	* (–)	—	* (–)
Protective action	***	* (–)	—	—	* (–)
Awareness	—	—	—	—	* (–)
Information	—	—	—	—	—
Adjustment	***	—	**	***	***
Preparedness	* (–)	—	***	***	***
Model	Multinomial	Binomial	Multinomial	Binomial	Multinomial
Pseudo R <sup>2</sup>	0.52	0.05	0.11	0.35	0.51
N	3462	4500	4500	4500	4500

The following symbols represent the respective levels of statistical significant: — n.s., \* 5%, \*\* 1%, \*\*\* 0.1%

(–) Indicates that the only significant effect is answering “I don’t know” as opposed to the other answers to the question

better adjustment to relative flood exposure, and only cost appraisal is non-significant. The PADM inspired model (Table 4) has the best pseudo R<sup>2</sup>, and the non-significant proxies are not core to the theory, suggesting more explanatory power.

While EUT is less well adjusted to adaptation (living in a flood-proofed home), risk aversion is not significant which could be due to how risk aversion was constructed in the survey rather than being deduced from a hypothesized utility function. EUT is slightly better adjusted to the adaptation score, with all proxies being significant. PMT is better adjusted to adaptation, however the cost appraisal is not significant for living in a flood-proofed home. Similarly, PMT is also better adjusted to the adaptation score. While PADM has the better fit to adaptation score, only a minority of proxies are significant for living in a flood-proofed home (adaptation). However, this might not always be a proactive or deliberate action of the respondents as the home may have already been adapted when they moved in.

The ability of the three rationalist theories to explain variation in the intended emergency behaviour is not particularly profound across the theories. EUT, for example, was less successful at explaining the variation in emergency behaviour intentions as compared to tangible adaptive behaviour. PMT also did not explain emergency behaviours

consistently. PADM, despite much wider conceptualisation, also struggled as a theory to explaining emergency behaviours.

Overall, the comparison of the model fit points to PADM improving on the much simpler models of EUT and PMT, especially on the adaptation score (improvements might be marginal for the other questions).

## 4.2 Constructionist theories results

The HoP inspired model (Table 5) a very good degree of explanatory power for risk perceptions: the best pseudo  $R^2$  for relative flood exposure and perceived flood probabilities, albeit lower for perceived flood impact. Moreover, HoP appears to be relatively more effective at explaining the variation in the adaptation and adaptation score responses of the respondents, comparable to the PADM results, even though some proxies as age, education, single-headed households or housing are not significant.

The SCT inspired model (Table 6) has an ability to explain differences in the perceived flood exposure, probabilities, and the adaptation of respondents. As EUT, SCT is however less well adjusted to the adaptation score despite in both cases it being the core of the theory in terms of enhancing the capacity to act. Some proxies as single-headed households or living with children are not significant.

The CTR inspired models (Table 7) have a fair fit for explaining differences in adaptation, flood probabilities and perceived flood exposure. However, CTR has always a lower model adjustment compared to the other theories. Like the rationalist theories, the ability of the constructivist theories to explain the variation in the intended emergency behaviours is rather elusive for the theories, though the HoP presents a noticeable improvement in the adjustment to the variation in peoples intended behaviour.

## 4.3 4.3. Combined results

Moreover, we consider what happens when all the constructs from all six theories are combined as a further example of a constructionist theory as it doesn't have a pre-existing rationale to limit the driving factors. The results systematically reflect a better fit of the models (Table 8) as expected because including more variables should mean that a greater degree of variation should be explained. Previous experience is the only construct to retain significant relationships to all independent variables. When setting aside the results for emergency behaviour during a flood (for which all theories and even the combination of constructs has a substantially lower fit), self-efficacy, responsibility, length of residence, preparedness, as well as perceptions of flood exposure retain significant relationships to all the remaining independent variables. Conversely, when combining all explanations, age, income, social capital and knowledge of flood information campaign lose all their significant relationships. The constructs not significant for any of the independent variables are not reported in Table 8. However, care should be taken when understanding this sort of combined model due to the nature of cross-correlations and co-driving factors.

Finally, we compare the performance of all these adjusted models. In Table 9, Cohen's kappa assesses the agreement between the model's predictions and the measured answers from the 500 respondents randomly set aside. As expected, the model combining the constructs from all six theories has the best prediction rates. Then, while the Protective Action Decision Model (PADM) and the Hazards-of-Place (HoP) inspired regression models

**Table 5** Hazards-of-place results (HoP)

	Exposure	Probabilities	Impacts	Emergency behaviour	Emergency behaviour score	Adaptation	Adaptation score
Actual exposure	***	**	—	***	—	—	—
Exposure (direct)	***	***	***	—	* (-)	***	***
Exposure (indirect)	***	***	***	—	** (-)	**	***
Experience (direct)	***	***	—	* (-)	*	***	***
Experience (indirect)	***	***	*	*** (-)	* (-)	***	***
Place attachment	*	—	—	*	—	***	***
Length residence	***	***	—	*	—	**	***
Social networks	***	***	**	—	—	*	**
Preparedness	***	***	***	—	***	***	***
Age	—	—	—	—	—	—	—
Female	*	—	*	—	*	*	—
Education	***	*	—	—	—	—	—
Income	—	—	—	—	—	—	**
Language	***	***	—	—	—	**	***
Single-parent	**	—	—	—	—	—	—
Children	—	—	—	—	—	—	*
Disabled	—	—	—	—	—	—	*
Minority	* (-)	—	—	—	*	**	*
Housing type	*	—	—	***	***	*	—
Home size	—	—	*	***	* (-)	—	—
Renter	—	*	—	—	* (-)	—	—
Insurance	***	*	***	***	—	—	*
Model	Multinomial	Multinomial	Multinomial	Binomial	Multinomial	Binomial	Multinomial
Pseudo R <sup>2</sup>	0.52	0.55	0.25	0.10	0.14	0.34	0.52
N	3462	3094	3101	4500	4500	4500	4500

The following symbols represent the respective levels of statistical significant: — n.s., \* 5%, \*\* 1%, \*\*\* 0.1%

(-) Indicates that the only significant effect is answering “I don’t know” as opposed to the other answers to the question

**Table 6** Social capital theory results (SCT)

	Exposure	Probabilities	Impacts	Emergency behaviour	Emergency behaviour score	Adaptation	Adaptation score
Exposure (direct)	***	***	* (-)	**	—	*	***
Exposure (indirect)	**	***	*	—	* (-)	***	***
Length residence	***	***	***	—	—	*	***
Social networks	***	***	***	—	**	***	***
Social capital	***	***	***	*	—	—	* (-)
Social norms	***	***	***	—	***	***	***
Subjective norms	***	***	***	—	*** (-)	***	***
Responsibility	***	*	***	***	***	**	***
Age	—	—	—	—	*	—	—
Female	*	*	*	—	***	*	**
Education	**	*	—	—	—	—	—
Income	—	* (-)	—	—	—	* (-)	***
Language	**	***	—	***	—	**	***
Single-parent	—	—	—	—	—	*	—
Children	—	—	—	—	—	—	—
Disabled	—	—	—	—	* (-)	—	**
Minority	* (-)	—	—	**	*	*	**
Model	Multinomial	Multinomial	Multinomial	Binomial	Multinomial	Binomial	Multinomial
Pseudo R <sup>2</sup>	0.40	0.50	0.25	0.07	0.12	0.30	0.41
N	3462	3094	3101	4500	4500	4500	4500

The following symbols represent the respective levels of statistical significant: — n.s., \* 5%, \*\* 1%, \*\*\* 0.1%

(-) Indicates that the only significant effect is answering “I don’t know” as opposed to the other answers to the question

**Table 7** Cultural theory of risk results (CTR)

	Exposure	Probabilities	Impacts	Emergency behaviour	Emergency behaviour score	Adaptation	Adaptation score
Exposure (direct)	***	***	***	—	** (-)	***	***
Exposure (indirect)	***	***	***	—	** (-)	***	***
Egalitarian 1	*	—	—	—	—	—	—
Egalitarian 2	***	**	***	***	***	—	***
Fatalism 1	***	***	***	*	—	—	** (-)
Fatalism 2	—	*	**	—	***	—	—
Hierarchy 1	* (-)	***	—	*	—	—	***
Hierarchy 2	—	***	*	**	**	*	**
Individual 1	***	***	***	—	**	***	***
Individual 2	***	***	***	—	***	***	***
Model	Multinomial	Multinomial	Multinomial	Binomial	Multinomial	Binomial	Multinomial
Pseudo R <sup>2</sup>	0.36	0.46	0.24	0.05	0.11	0.30	0.39
N	3462	3094	3101	4500	4500	4500	4500

The following symbols represent the respective levels of statistical significant: — n.s., \* 5%, \*\* 1%, \*\*\* 0.1%

(-) Indicates that the only significant effect is answering “I don’t know” as opposed to the other answers to the question

**Table 8** Combined model results

	Exposure	Emergency behav- iour	Emergency behaviour score	Adaptation	Adaptation score
Previous experience (indirect)	***	***	***	***	***
Exposure (direct)	***		*	***	**
Self-efficacy	***		**	***	***
Preparedness	**		***	***	***
Responsibility	**	***	***		
Exposure (actual)	***	***			
Length residence	**			**	***
Experience (direct)	**			***	***
Insurance	***	*			
Probabilities	***				***
Worry	***				*
Protective action	***				*
Flood severity	***				
Control	***				
Flood consequences	***				
Education	**				
Cost appraisal		***	***		*
Place attachment		*		***	***
Home size		***	***	**	
Disability		***	***		
Minority			*	**	
Risk aversion			***		
Female			*		
Renter			*		
Exposure (indirect)				*	**
Single-parent				*	
Language				**	
Social networks				*	
Awareness					*
Children					*
Model	Multinomial	Binomial	Multinomial	Multinomial	Multinomial
Pseudo R <sup>2</sup>	0.53	0.10	0.14	0.35	0.53
N	3462	4500	4500	4500	4500

The following symbols represent the respective levels of statistical significant: \* 5%, \*\* 1%, \*\*\* 0.1%

reach similar levels, the models adjusted on the constructs from the other theories prove to be less often in agreement with the measured values. However, further confirming previous results, none of the models had the capacity to accurately predict the variation regarding the emergency behaviours of the respondents.

**Table 9** Comparison of the models' performance (Cohen's kappa)

	Exposure	Emergency behaviour	Emergency behaviour score	Adaptation	Adaptation score
Combined	0.42***	0.03	0.04	0.42**	0.31**
PADM	0.39***	—	—	0.37**	0.29**
HoP	0.37***	—	—	0.41**	0.26**
PMT	0.34***	—	—	0.31*	0.24*
SCT	0.29***	—	—	0.31*	0.24*
CTR	0.29***	—	—	0.35*	0.20
EUT	0.33***	—	—	0.26*	0.14

The following symbols represent the respective levels of statistical significant: — n.s., \* 5%, \*\* 1%, \*\*\* 0.1%

## 5 Discussion

### 5.1 Theory comparison

The primary objective of this paper was to operationalise and explore the relative ability of six different behavioural theories to explain the variability in the respondents' flood risk adaptation, emergency behaviour intentions, and where possible a range of risk perceptions. Overall, we found that explanatory power varied substantially across risk perceptions and adaptive behaviours for a given theory, and across theories for a given aspect of perception or behaviour. This variation across perceptions or behaviours demonstrates that theories differ in their efficacy to explain aspects of the variation in risk perceptions or behaviour across respondents. We posit that this is because specific perceptions or behaviours might be better suited than others to certain theories as a result of the combination of question constructs employed by the theory. Therefore, it is not an arbitrary choice regarding the choice of a theoretical baseline in terms of the explanatory power.

The Protective Action Decision Model (PADM) and the Hazards-of-Place (HoP) inspired regression models have the best predictive performance and describe the largest amount of observed variability within the data concerning observed adaptive behaviour and risk perceptions. Part of this outcome is driven by the observation that these two theories are the most flexible and context adaptable theories. For instance, while PADM has a central core of socio-psychological variables deemed to be applicable across studies due to its core set of informational cues and drivers (as required by the rationalist approach), the theory also contains an element of the constructivist approach via framing factors module which allows for additional explanatory variables to be added that make sense for the local context (Lindell and Perry 2012) in a way that EUT or PMT do not. HoP has a similarly flexible set of guiding principles due to how it has effectively evolved into a social vulnerability framework, which in turn must be rooted in the local context to be effective (Cutter et al 2008). Therefore, the combination of these two theories could be a way for a more systematic theory construction and comparability across studies due to an existing understanding in the scientific literature on the considerations of constructing a social vulnerability indicator or set of variables. While this proposal may add more structure, one of the limitations of combining these two theories is their potential to be quite expansive and multidimensional (as compared to the relatively parsimonious PMT). For instance, social vulnerability is a highly complex and situational concept that cannot be overly simplified

(Burton et al., 2018). Therefore, this may result in an operationalised framework that captures multiple different angles complicating the combined theory's implementation. However, because of the constructionist nature of social vulnerability, developing and implementing behavioural theories research shows that the process of selecting variables will not be completely comparable across applications as it might be context-dependent (Rufat et al. 2019; Spielman et al. 2020).

While these two theories may be a successful combination moving forwards, due to being located at an intersection point of various theories along the rationalist and constructivist spectrum, one caveat is the relatively limited marginal value of expanding the number of constructs included in the models. The improvement in our ability to describe the variation in answers is relatively modest compared to the outcome with only relevant PADM and HoP variables. Moreover, even in this relatively modest improvement is still limited as at best 47% of the variation remains unexplained. Therefore, there remains elements of the process that generates risk perceptions or drives adaptation behaviour still missing from the selected behaviour theories.

A further observation in this vein is that none of the theories had the capacity to explain the variation regarding the emergency behaviours of the respondents. This is true across the behavioural models and therefore a different behavioural model maybe required, a specific extension for emergency behaviour that captures a range of different behavioural drivers. For instance, Kreibich et al. (2021) evaluate the success of flood emergency warning systems across a series of floods in Germany. They found that despite having a sufficient lead time the emergency warning system only promoted a successful reduction of flood damage if the respondent was confident in their pre-existing actionable knowledge of what to do before they received the message. Therefore, future extensions of the investigated behavioural theories may have to place a greater emphasis on the information seeking, retention, and actionability in explaining the emergency behaviour of those impacted by flooding. However, when explaining overall evacuation decisions rather than specific emergency behaviour (e.g. getting their car from the street during a flood) like in our study, previous studies found that PADM had a better fit than in our results (Huang et al. 2017). Additionally, a different surveying approach may be more successful at capturing emergency behaviour than surveying intentions at timepoints rather removed from the context and psychological pressures of making their emergency decisions. For instance, an approach like in Botzen et al. (2024) who use near real time surveys of people threatened by hurricanes as this places the survey respondent in a more similar decision-making position and context.

## 5.2 Limitations and future research directions

This paper considered how the 6 selected theories could perform across various applications following the ways theory is often applied within the literature. The theory driven approach and the focus on the overall model performance in general, rather than the specific variable or context-led implications of the model, allows for these results to be generalisable. However, there should remain an element of caution because without a sample covering multiple countries and/or hazards (like Noll et al., 2023) we cannot directly confirm that these results will hold due to different place-based consideration.

Additionally, there are limits to the construction and operationalisation of the theories in an empirical sense. This is because the rationalist theories have a relatively well and narrowly defined behavioural core that can be clearly operationalised. However, the constructivist theories and their construction in an empirical sense is relatively more challenging

due to their loosely defined conceptual core. Part of this challenge manifested during the process of designing questions in the survey to capture the sometimes-overlapping constructs from the different theories, introducing an element of measurement error. Another aspect is in understanding the “correct way” that the concepts should be measured so that the theory is comprehensively measured in a way that suits local context and needs. In this application of the theories SCT and CTR suffered from this issue most strongly. However, there may be an argument that the HoP model can capture elements of these two models in the constructivist approach. For example, models of social vulnerability can include that more socially vulnerable individuals may have less bridging and linking stocks of social capital, while the CTR will filter through how the researcher understands what should be considered as socially vulnerable given local cultural nuances.

One future research direction would be the modelling of behaviour theories via Structural Equation Modelling (SEM). It allows to evaluate theoretical models that include direct and indirect relationships, feedback loops, and hierarchical structures. These features are present in various behavioural theories to different extents (e.g., PADM has a formal feedback loop, while PMT does not). However, SEM is focused on causal rather than predictive understandings, it may not be possible to estimate a model from any given dataset, and comparing the theory’s performance on the same dataset might prove to be quite challenging.

Additionally, a further research direction would be to conduct a replication study in a different regional and/or hazard context for two reasons. The first is that a matching replication would support which of the theories are more relatively “successful”, but secondly it would provide evidence towards the core drive of the rationalist paradigm in universal rules and expectations holding.

## 6 Conclusion

Flooding is a significant, pressing, and complex threat that must be proactively managed and mitigated. Impacts from flooding are expected to increase due to climate change and continued development in flood-prone areas. One key element to mitigate the risks is the behaviour of households and their pre-flood level of preparedness and adaptation. However, the current scientific literature on flood preparedness behaviour is highly fragmented in terms of its scope, approach, and theoretical underpinnings. While fragmentation occurs due to the needs of individual research questions and contexts, the involvement of various disciplines shaped by different sets of assumptions, the results produced can be difficult to compare across studies. This is particularly problematic if we wish to compare the different capabilities of the competing behavioural theories often studied, because they are implemented on different respondents instead of empirically compared. We address this gap by comparing a range of the capability of six behavioural theories on a large dataset of 5000 respondents following a series of floods in Paris, France, to describe the observed variability in respondent’s risk perceptions and preparedness behaviours. In doing so we find that the Protective Action Decision Model (PADM) and the Hazards-of-Place (HoP) inspired models have the best predictive performance and describe the largest amount of observed variability within the data. This suggests that social vulnerability explains a significant part of risk perceptions and adaptive behaviour that are not always captured by rational choice and psychological models. However, none of the tested theories were particularly effective at describing the observed variability in the emergency behaviour variables. We

further posit that the rationalist and constructivist approaches could be combined to further refine the theoretical frameworks. Specifically, the PADM and the HoP are also suitable for being integrated together in future research. This is because the framing factors module of PADM rather than being loosely defined could benefit from the structured approach that HoP (and social vulnerability) provide while still being adaptable to local contexts; a combination possible due to the observation of rationalist and constructionist paradigms operating along a conceptual spectrum. Therefore, it seems plausible that a further refinement of the currently most employed behavioural models is required to explain more successfully behavioural during a flood, and especially emergency behaviour that has also drawn comparatively less focus in the scientific literature.

## Appendix

See Tables 10 and 11.

**Table 10** List of independent variables

Variable	Description
Age	What is your age group?
Awareness	Do you remember any event or information campaign on flood risks?
Children	Do you live with children under the age of 12? How many?
Cost appraisal	How much do you estimate the total cost of damage if your home was flooded (including damage to property inside the home)?
Disability	Do you or someone in you household live with a disability?
Education	What is your level of education?
Egalitarianism 1	On a scale of 1 to 5, can you count on the help of friends, neighbours or relatives when you need it?
Egalitarianism 2	In case of flooding, who do you feel responsible for in terms of safety? (score)
Exposure (actual)	[not a question] derived from the location of the respondent's home inside or outside of the official flood delineation
Exposure (perceived, direct)	Is your home in a flood zone?
Exposure (perceived, indirect)	In the event of flooding, could your home be indirectly affected by power cuts?
Fatalism 1	On a scale of 1 to 5, are the measures to be taken to limit the effects of flooding on my home rather rely on me... on public authorities
Fatalism 2	On a scale of 1 to 5, how much risk are you willing to take in general?
Female	What is your gender?
Hazard adjustment	Do you know what you can do to limit the effects of flooding on your home?
Hierarchy 1	Who do you trust most to inform you in case of a crisis or disaster? (score)
Hierarchy 2	Who do you trust most with evacuation instructions in the event of a crisis or disaster? (score)
House size	What is the size of your accommodation?
Housing	What type of housing do you live in?
Income	What is approximately the annual income level of your whole household?
Individualism 1	On a scale of 1 to 5, do you know what you can do to limit the effects of flooding on your home?
Individualism 2	In the event of flooding, how would you rate your household's level of preparedness? (5-score)

**Table 10** (continued)

Variable	Description
Information	Are you aware of any official information on the risks?
Insurance	Is your home insured?
Language proficiency	On a scale of 1 to 5, how comfortable are you with writing and speaking French?
Length of residence	How long have you lived in the same place?
Minority	Are you a member of a visible minority who might be discriminated against?
Protective action	On a scale of 1 to 5, are the measures to be taken to limit the effects of flooding on my home rather rely on me... on public authorities
Perceived consequences	In your neighbourhood, can floods have serious consequences?
Perceived control	In your neighbourhood, are floods easy or difficult to control?
Perceived payoffs	How much do you estimate the total cost of damage if your home was flooded (including damage to property inside the home)?
Perceived prediction	In your neighbourhood, how easy or difficult is it to predict flooding?
Perceived probabilities	In your neighbourhood, how often does flooding occur?
Perceived severity	In your neighbourhood, can floods have serious consequences?
Place attachment	What do you like most about your neighbourhood? (score of positive items)
Preparedness	In the event of flooding, how would you rate your household's level of preparedness?
Previous experience (direct)	Have you been affected by floods in the last ten years?
Previous experience (indirect)	Have you ever experienced an unpredictable power, water or heating cut lasting several days?
Renter	Are you an owner or a tenant?
Response efficacy	In the event of flooding, how would you rate your household's level of preparedness?
Responsibility	In case of flooding, who do you feel responsible for in terms of safety?
Risk aversion	On a scale of 1 to 5, how much risk are you willing to take in general?
Self-efficacy	On a scale of 1 to 5, do you know what you can do to limit the effects of flooding on your home?
Single-parent	Are you a single-parent family?
Social capital	On a scale of 1 to 5, can you count on the help of friends, neighbours or relatives when you need it?
Social network	On a scale of 1 to 5, when you go out or do your shopping in the neighbourhood, how often do you meet friends or relatives?
Social norms	On a scale of 1 to 5, do you know what you can do to limit the effects of flooding on your home?
Subjective norms	In case of flooding, who do you feel responsible for in terms of safety?
Threat perception	In your neighbourhood, how long can a flood last?
Worry	Do you worry about floods?

**Table 11** Summary of variables included in each theory lead model

Variable	Expected Utility Theory	Protection Motivation Theory	Protective Action Decision Model	Hazards of Place	Social Capital Theory	Cultural Theory of Risk
Probabilities	X	X	X			
Consequences	X	X	X			
Payoffs	X					
Self-efficacy	X	X				
Risk aversion	X					
Perceived exposure (direct)		X	X	X	X	X
Perceived expo (indirect)		X	X	X	X	X
Experience (direct)		X	X	X		
Experience (indirect)			X	X		
Cost appraisal		X	X			
Self-efficacy		X				
Response-efficacy		X				
Worry			X			
Threat			X			
Control			X			
Protective action			X			
Awareness			X			
Information			X			
Adjustment			X			
Preparedness			X	X		
Actual exposure				X		
Place attachment				X		
Length of residence				X	X	
Social Network				X		
Age				X	X	
Female				X	X	
Education				X	X	
Income				X	X	
Language				X	X	
Single-parent				X	X	
Children				X	X	
Disabled				X	X	
Minority				X	X	
Housing type				X		
Home size				X		
Renter				X		
Insurance				X		
Responsibility					X	
Subjective norms					X	
Social norms					X	
Social capital					X	

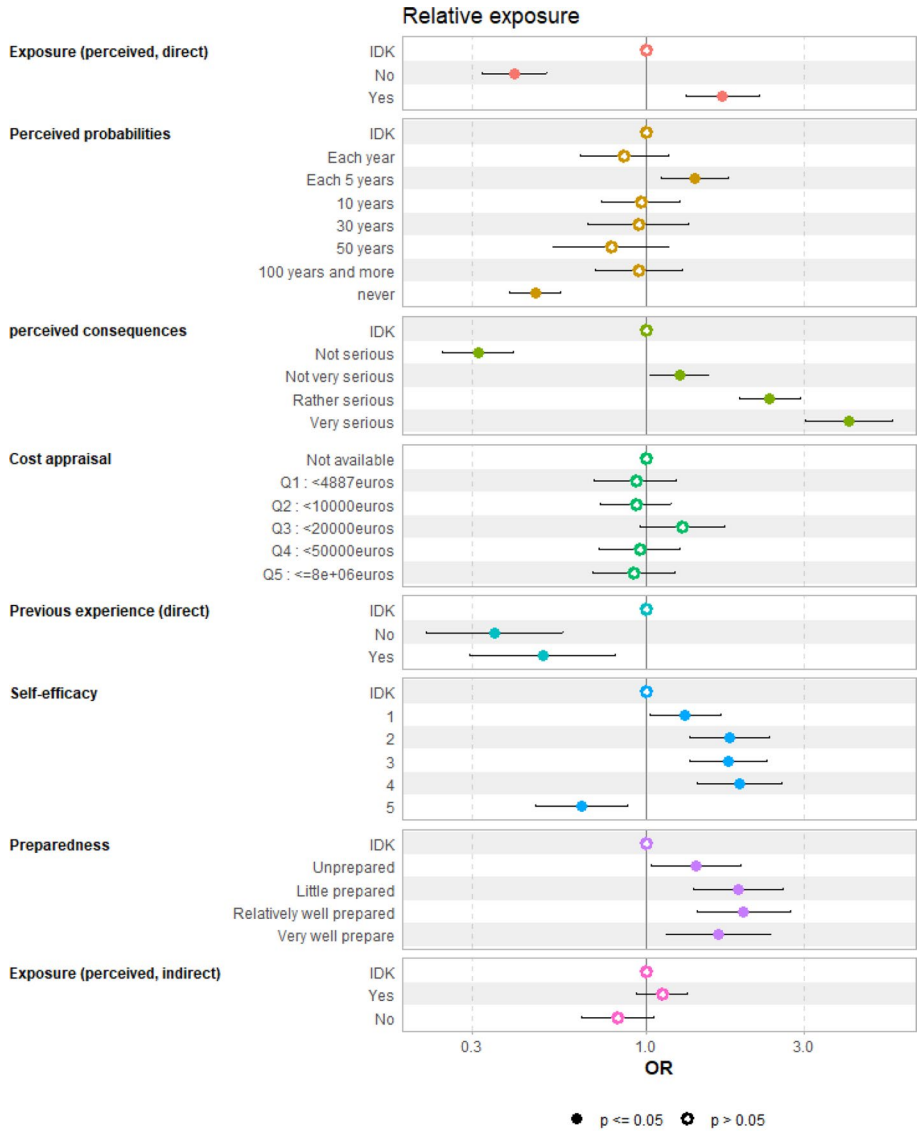
**Table 11** (continued)

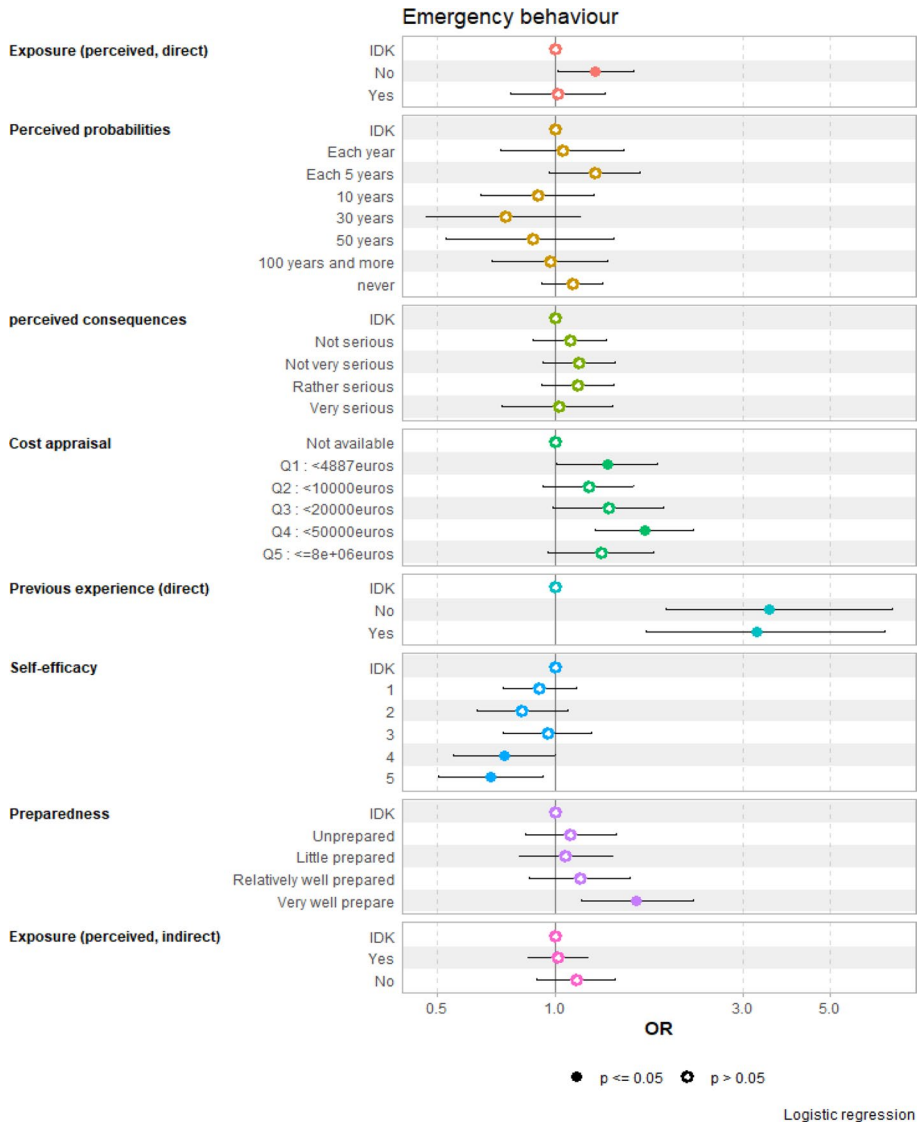
Variable	Expected Utility Theory	Protection Motivation Theory	Protective Action Decision Model	Hazards of Place	Social Capital Theory	Cultural Theory of Risk
Egalitarian 1						X
Egalitarian 2						X
Fatalism 1						X
Fatalism 2						X
Hierarchy 1						X
Hierarchy 2						X
Individual 1						X
Individual 2						X

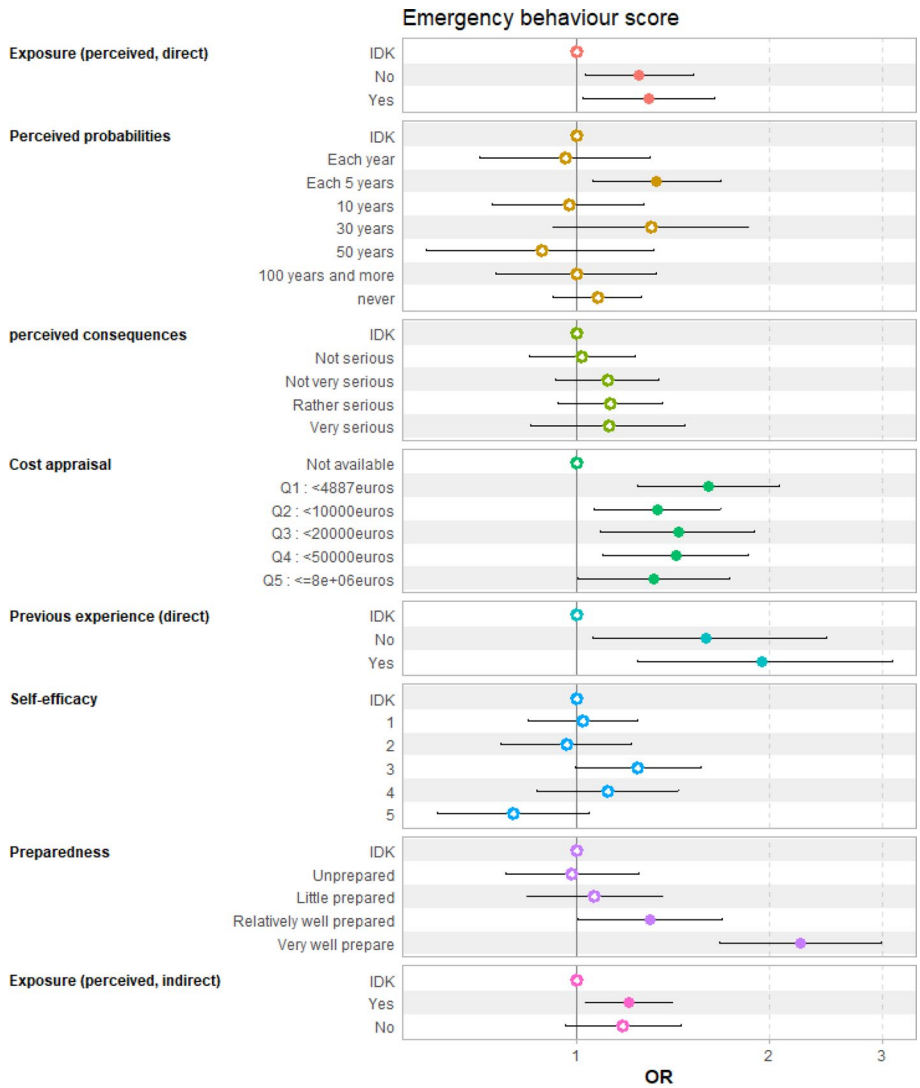
### Detail of the directionality of the results

We plotted the odds ratio for all the reference models from the paper for each theory. Each model compares the odds of each answer to an explanatory variable relative to a reference factor. The reference is represented by the vertical line and the odds ratio are plotted as a dots. The distribution function is of the logit type, measuring the effect of each answer while isolating it from the effects of the other explanatory variables included in the model. This an "all other things being equal" analysis, where greater values (to the right) mean that people giving that specific answer to the explanatory variable are more likely to also give the expected answer to the independent variable, whereas lower values (to the left) mean that they are more likely to give the opposite answer. The confidence intervals (95%) are also plotted as lines sticking out of the dot. If the confidence intervals overlap with the vertical line for the comparison group, their answer to the independent variable does not diverge significantly. Moreover, to avoid implicit selection bias, we have retained the "I don't know" answers for the explanatory variable. In order to measure the impact of these "I don't know", i.e. assess if the only significant information is provided by the "I don't know" answer, we performed a complementary analysis, testing if the significance of all likelihood ratios withstood the removal of these answers from a variable. For each explanatory variable in each model, we constructed an additional model whose parameters remain strictly identical to the reference model, with the exception of the removal of the "I don't know" answers from the variable under examination. We report if the significance is maintained and interpret the loss as indication that the only significant information provided by this specific explanatory variable in this models stems from the "I don't know" answer.

PMT



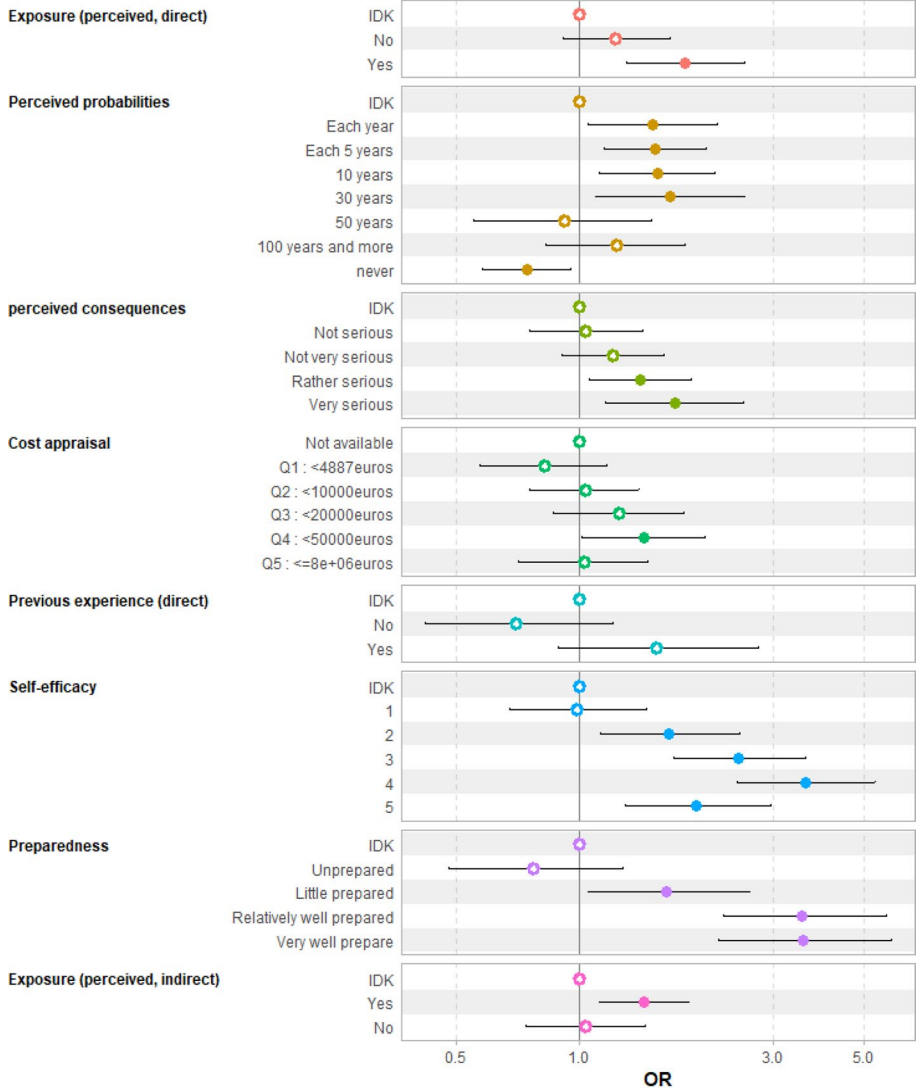




● p <= 0.05   ○ p > 0.05

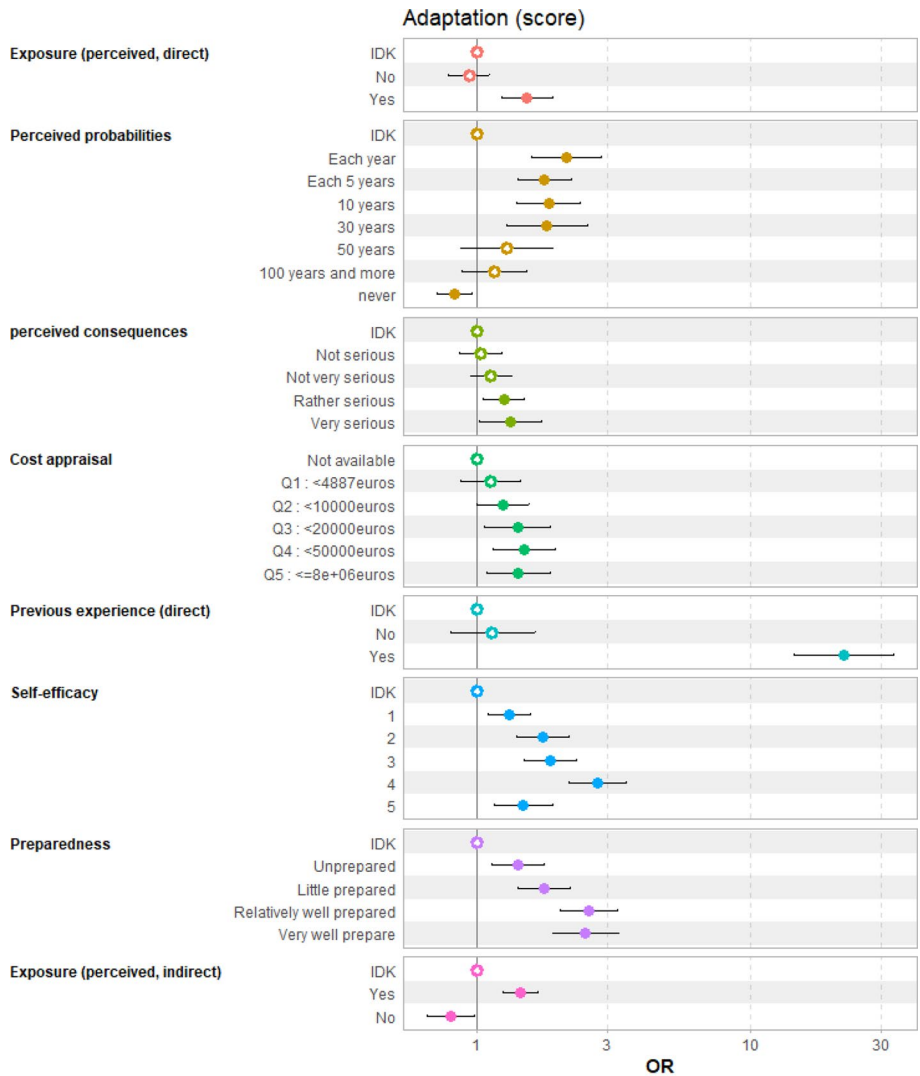
thresholds : 0|1 1.8211 1|2 3.6189 2|3 5.2219 3|4 6.2218

Adaptation



● p <= 0.05 ○ p > 0.05

Logistic regression

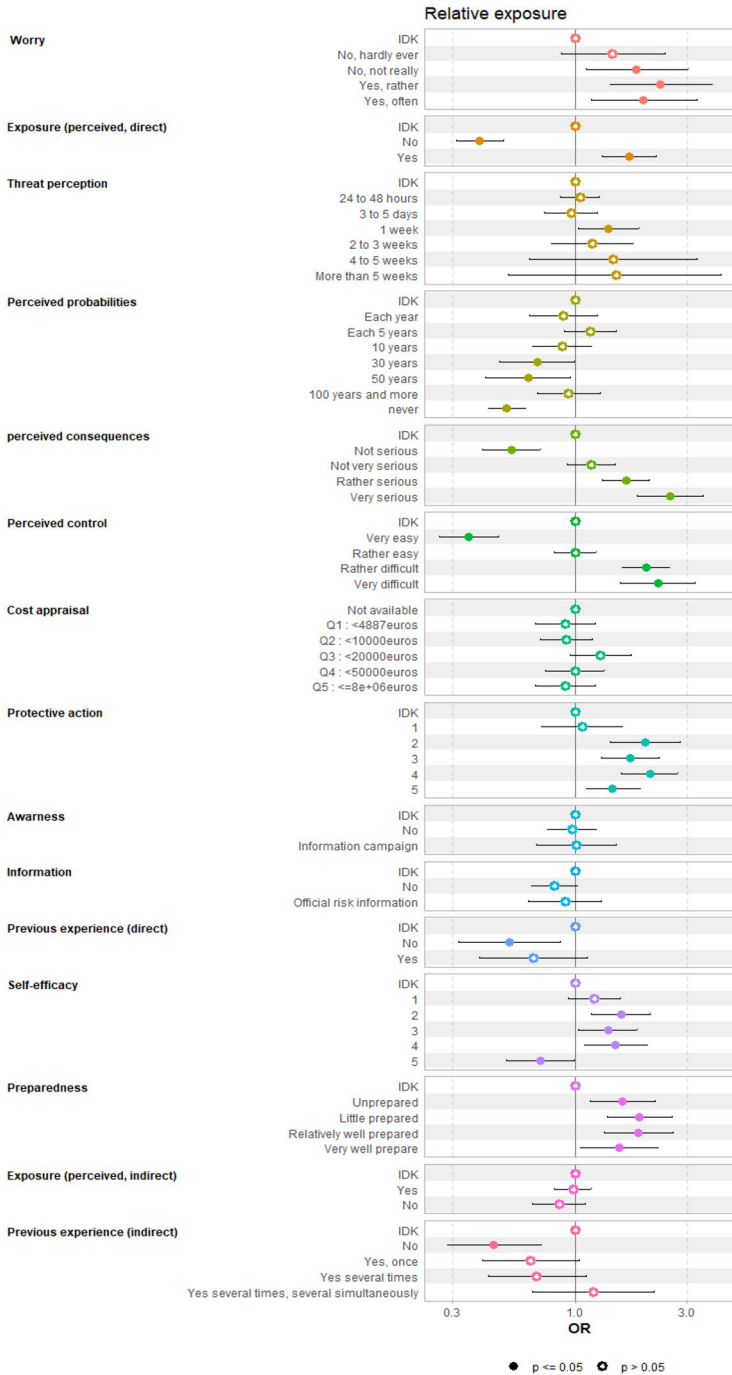


● p <= 0.05    ○ p > 0.05

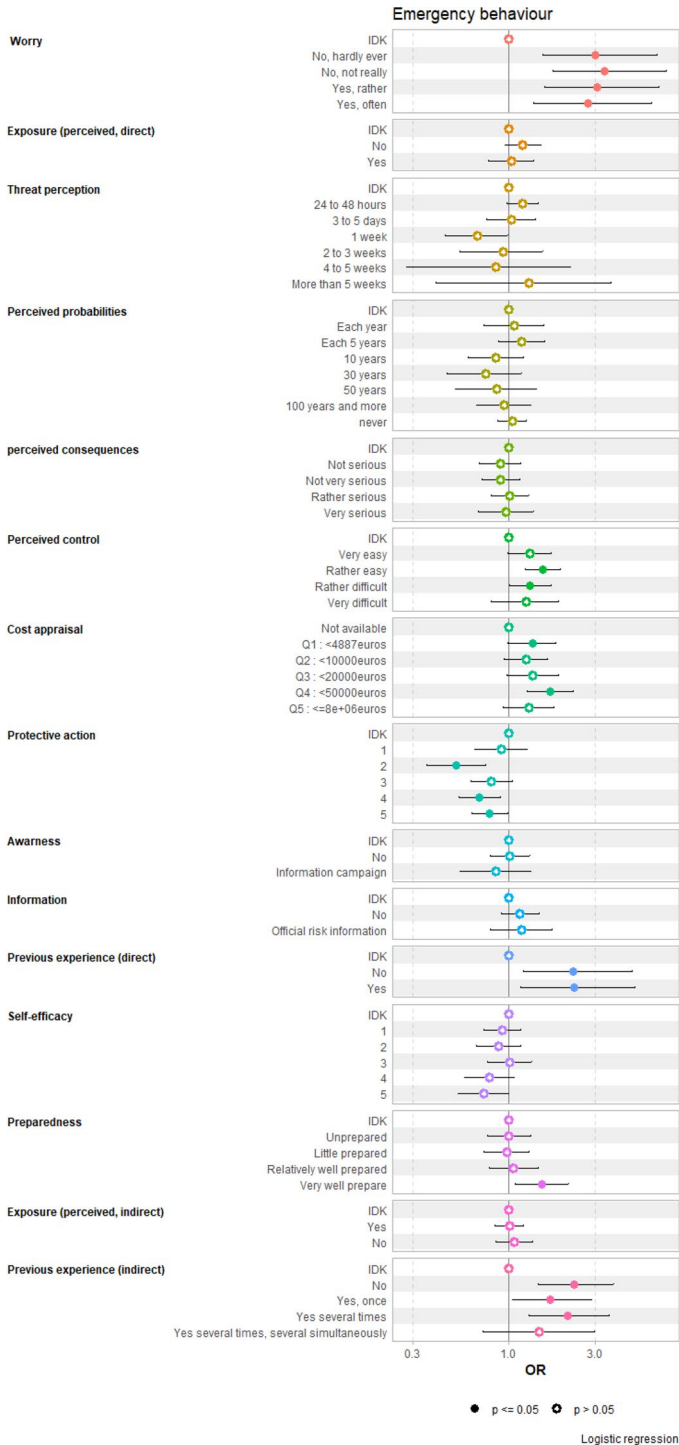
thresholds : 0|1 0.8432 1|2 3.7773 2|3 6.0967 3|4 7.7159 4|5 9.3053  
5|6 11.478

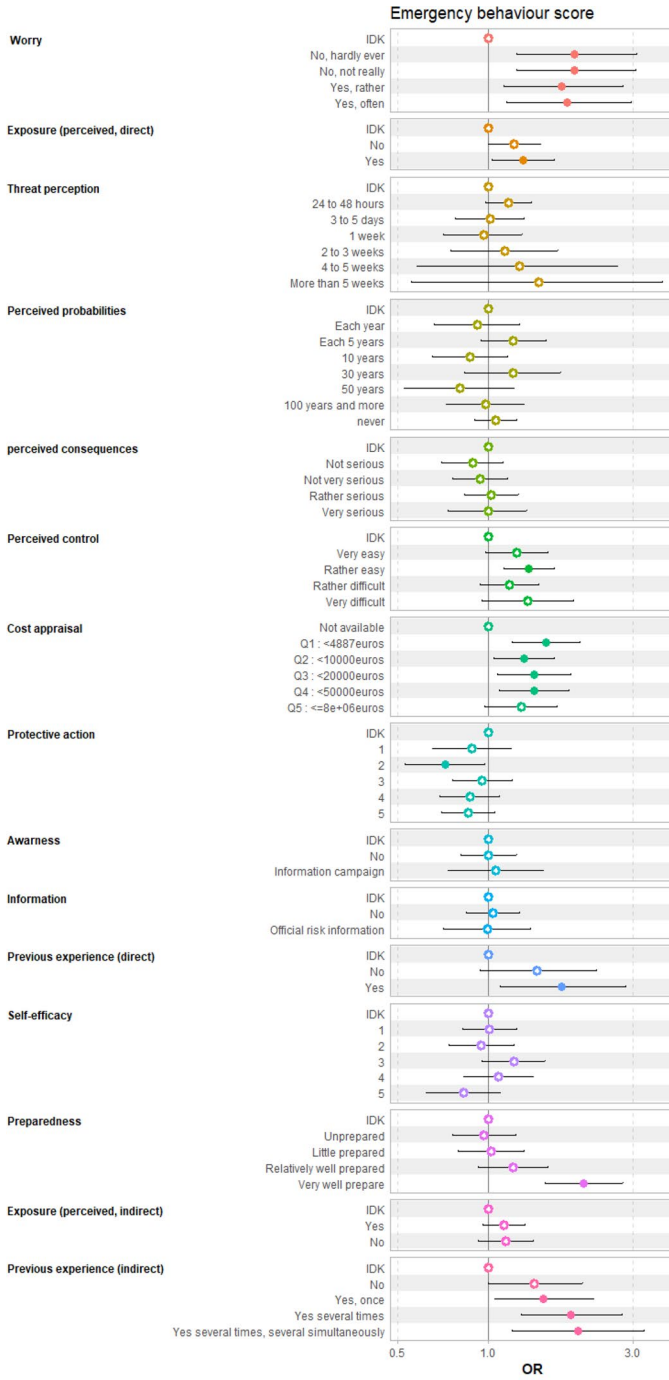
PADM

PADM

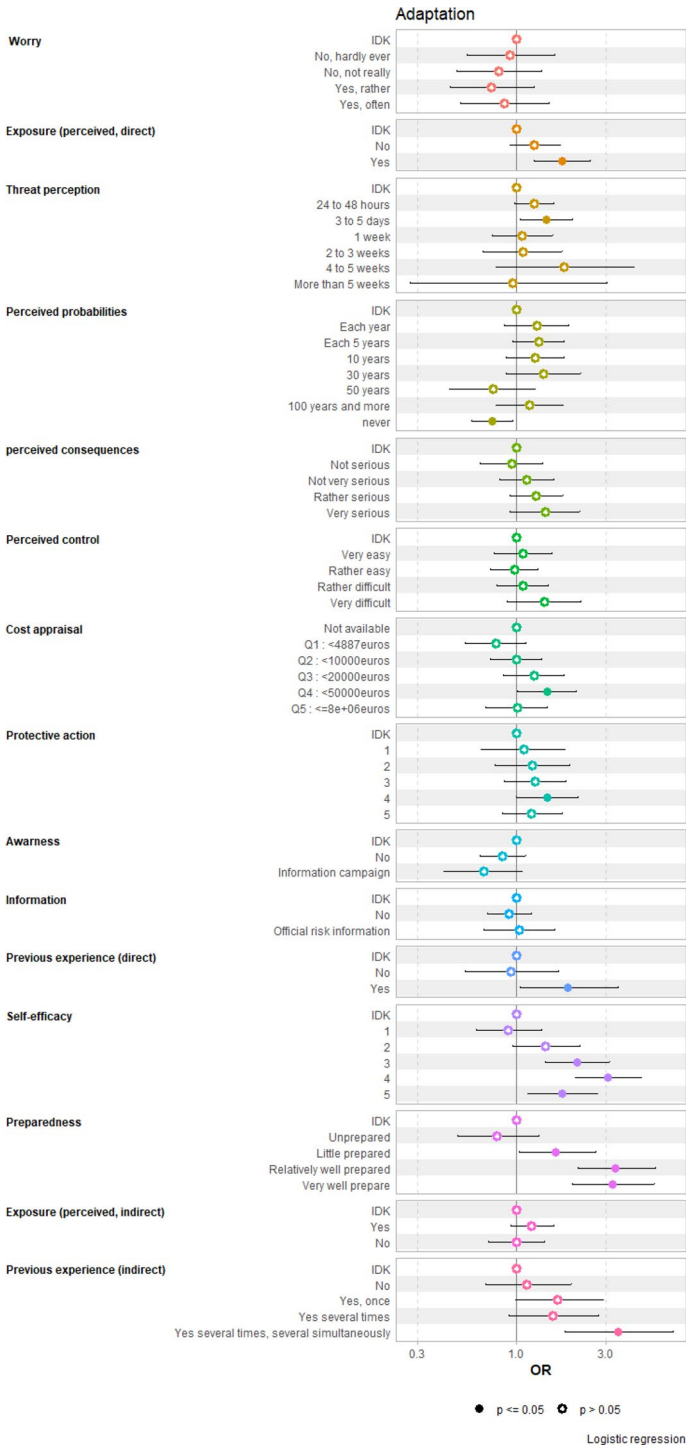


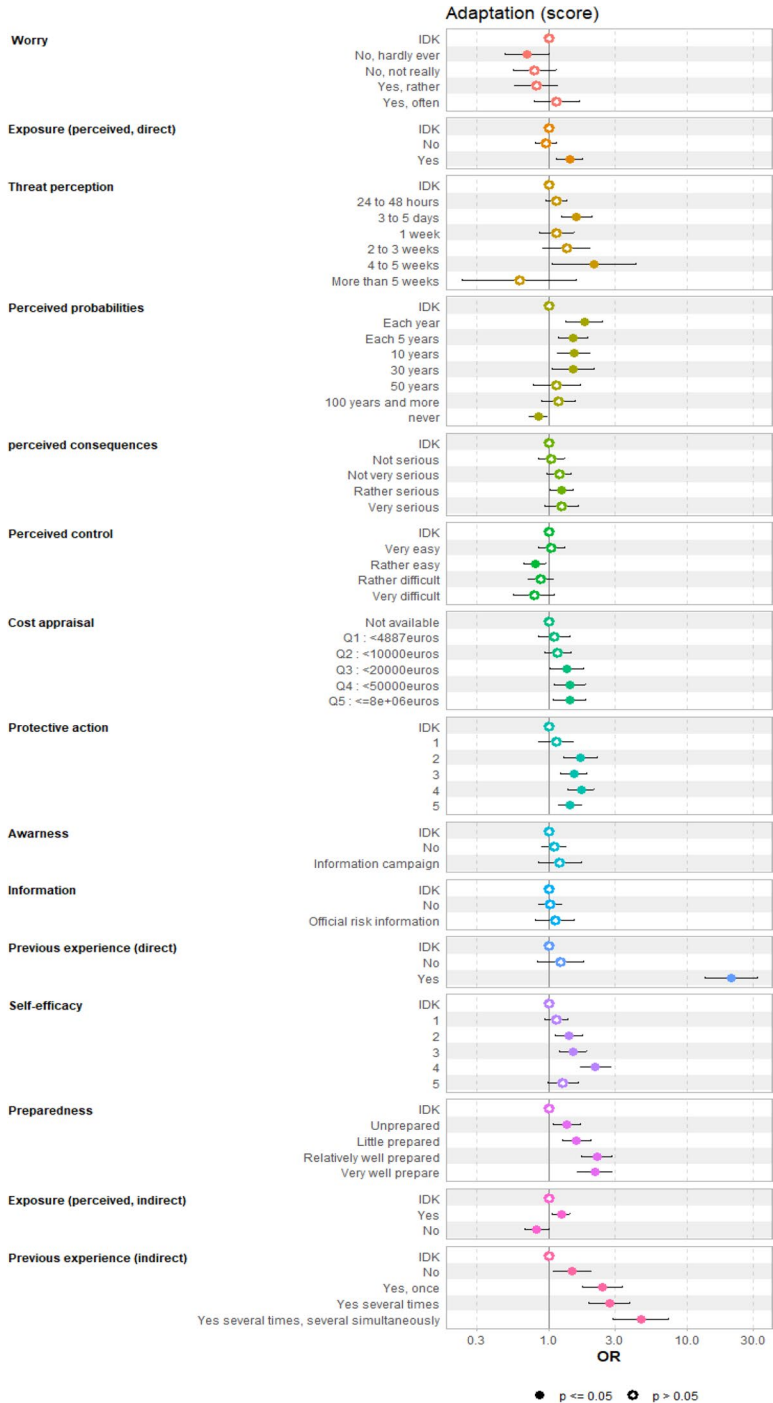
thresholds : Much less exposed|A little less -0.7007 A little less|A little more 1.3391 A little more|Much more exposed 3.6446





● p <= 0.05 ○ p > 0.05  
 thresholds : 0|1 2.562 1|2 4.3709 2|3 5.9769 3|4 6.9783

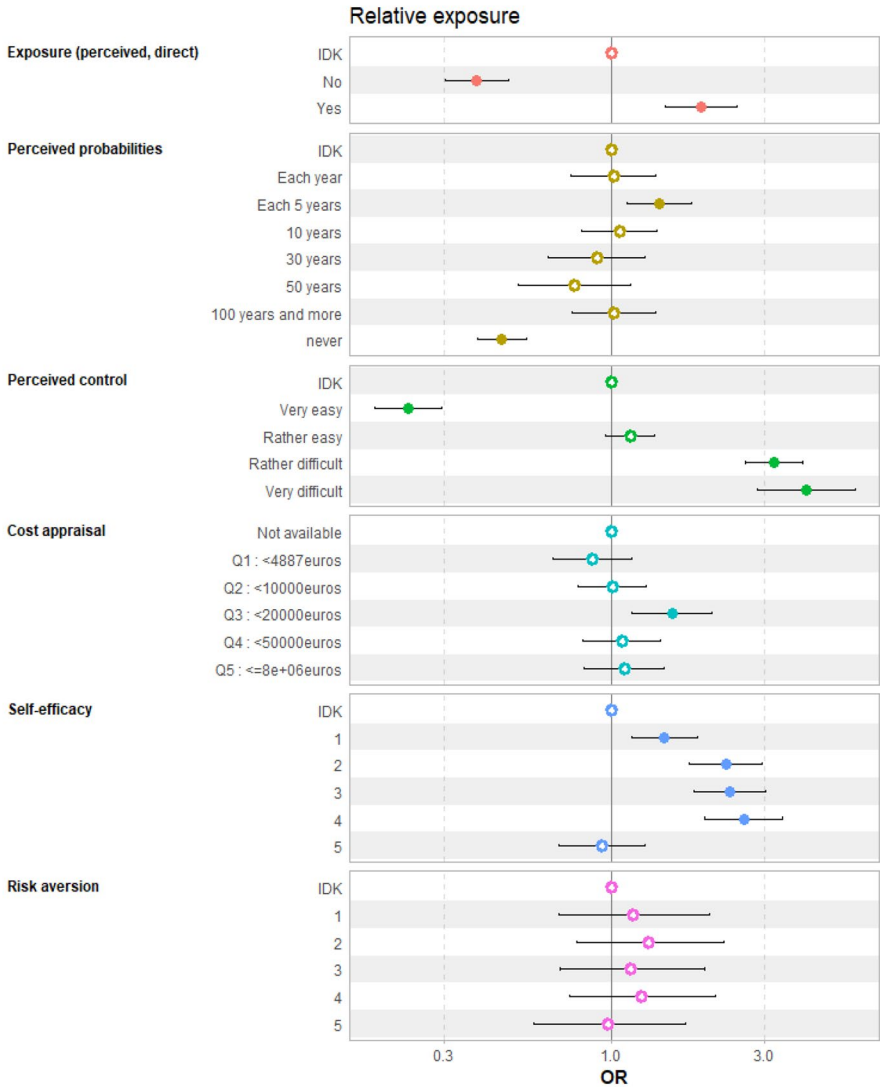




thresholds : 0|1 1.2068 1|2 4.2263 2|3 6.6253 3|4 8.2953 4|5 9.9045 5|6 12.0838

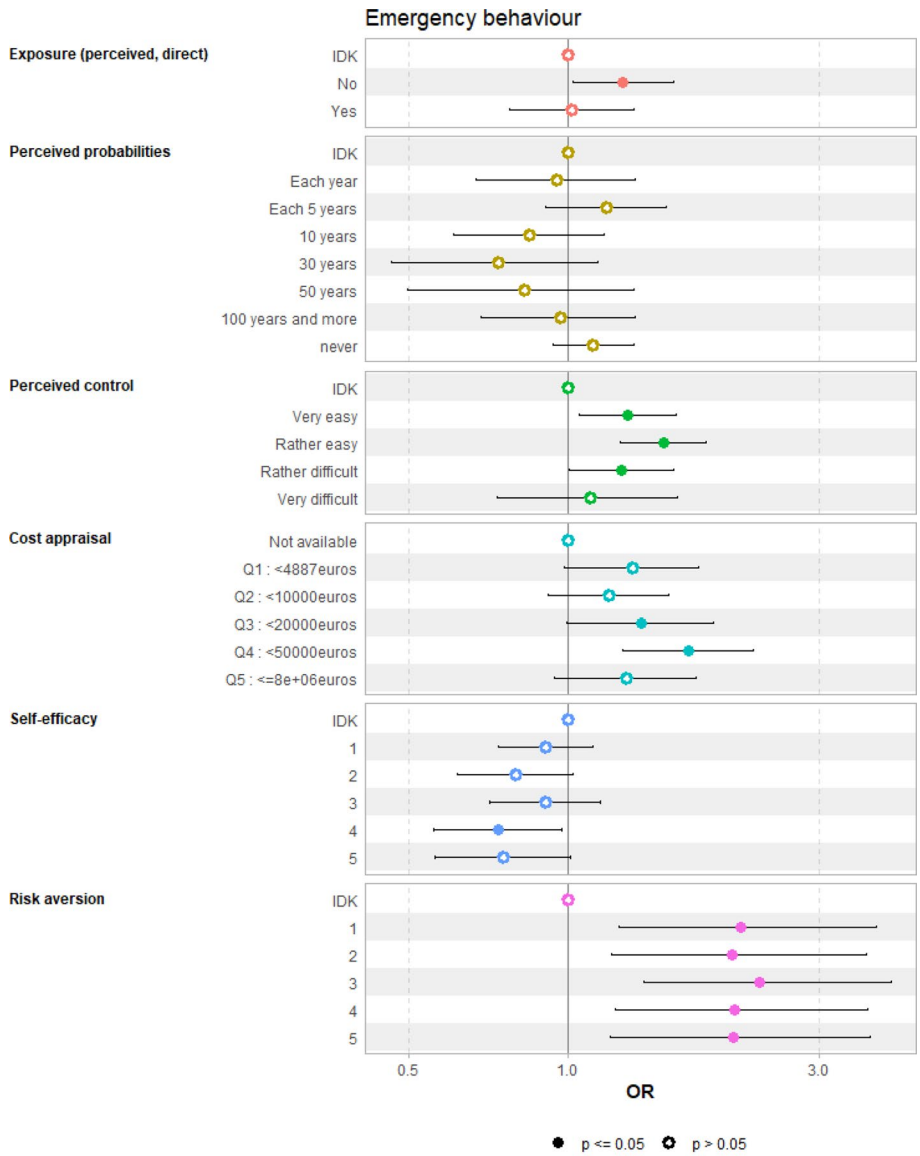
EUT

EUT

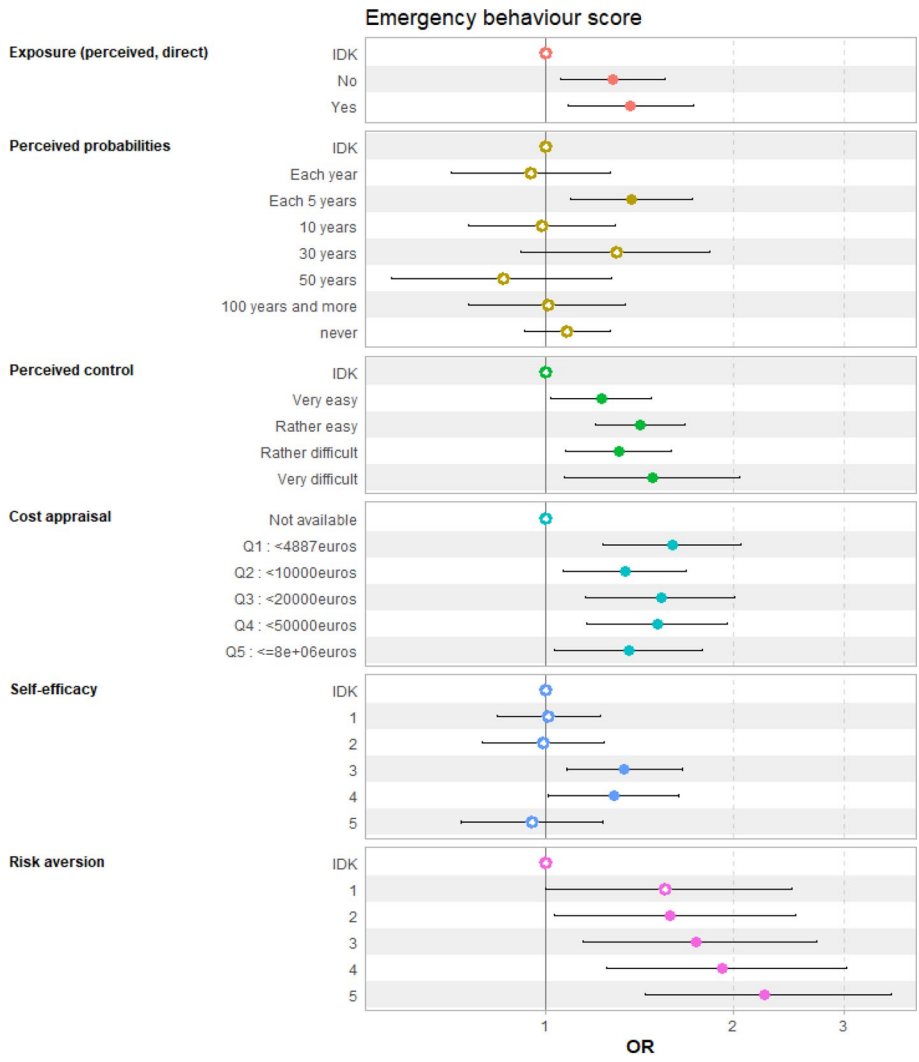


● p <= 0.05 ○ p > 0.05

thresholds : Much less exposed|A little less -0.3333 A little less|A little more 1.581 A little more|Much more exposed 3.7894

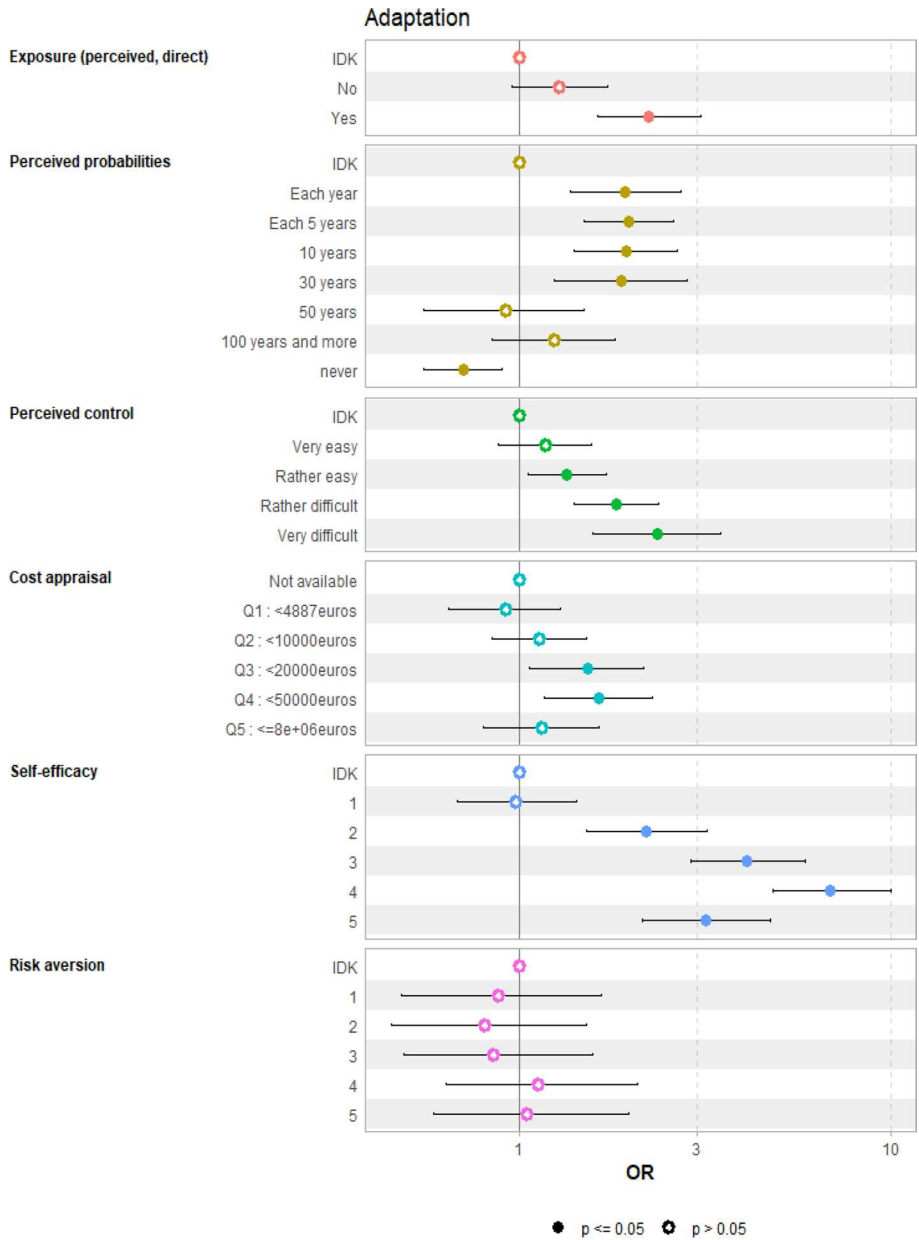


Logistic regression

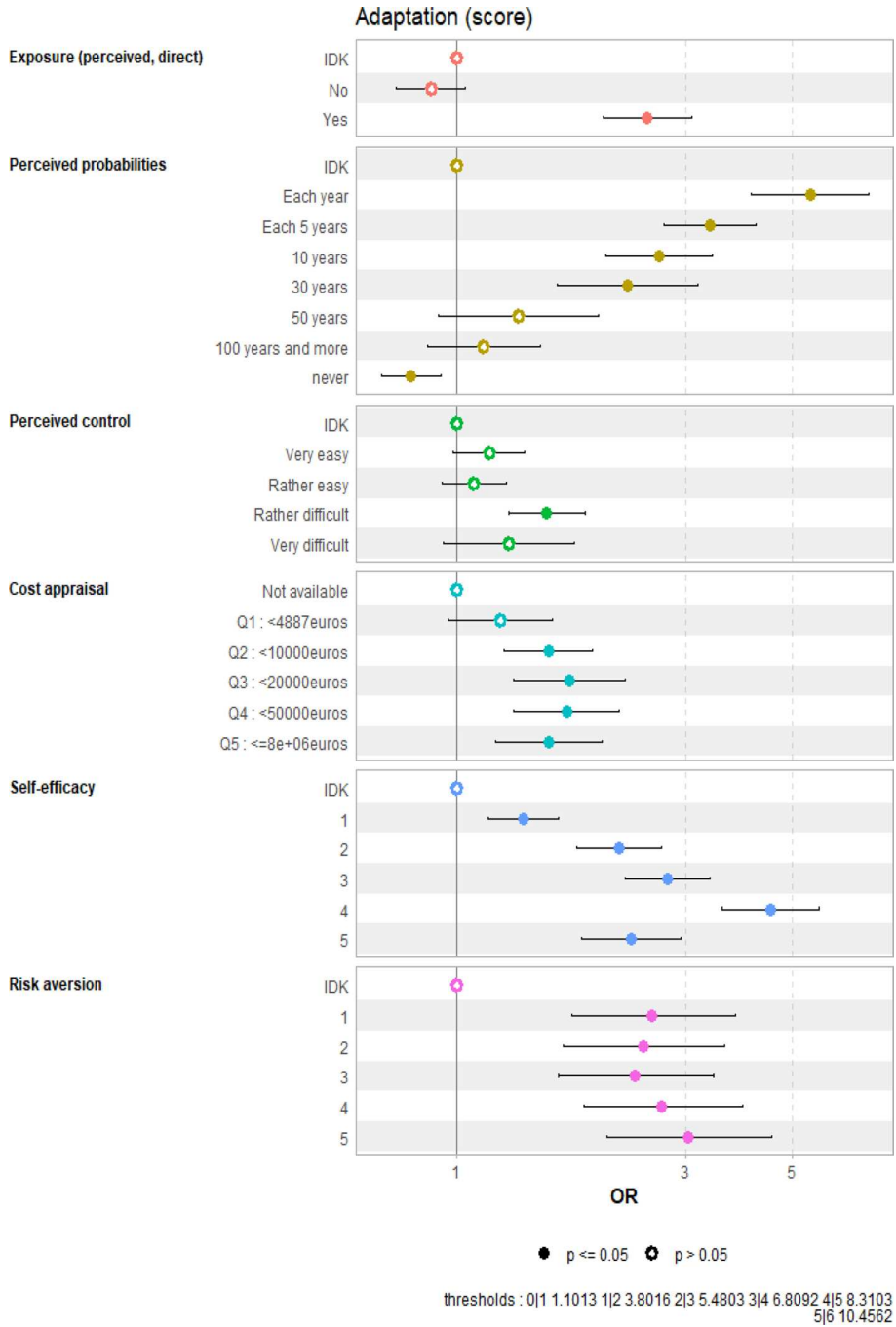


● p <= 0.05 ○ p > 0.05

thresholds : 0|1 1.8152 1|2 3.6031 2|3 5.2025 3|4 6.2001

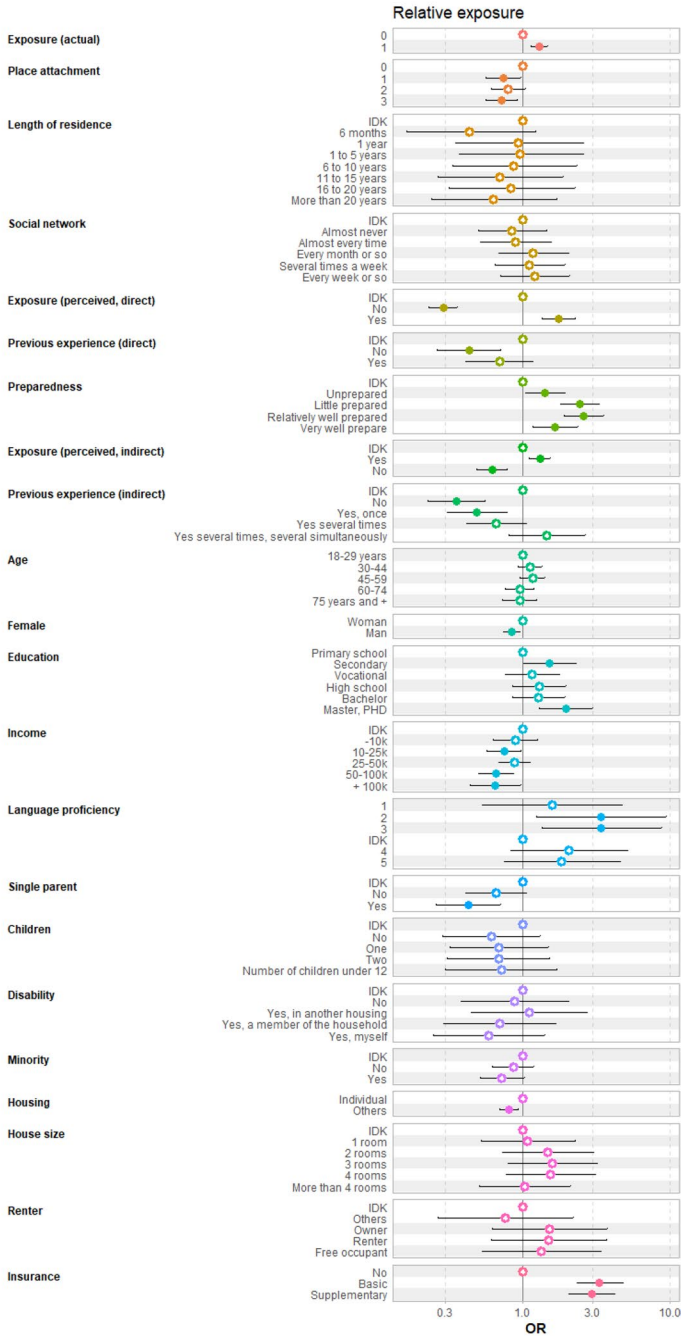


Logistic regression

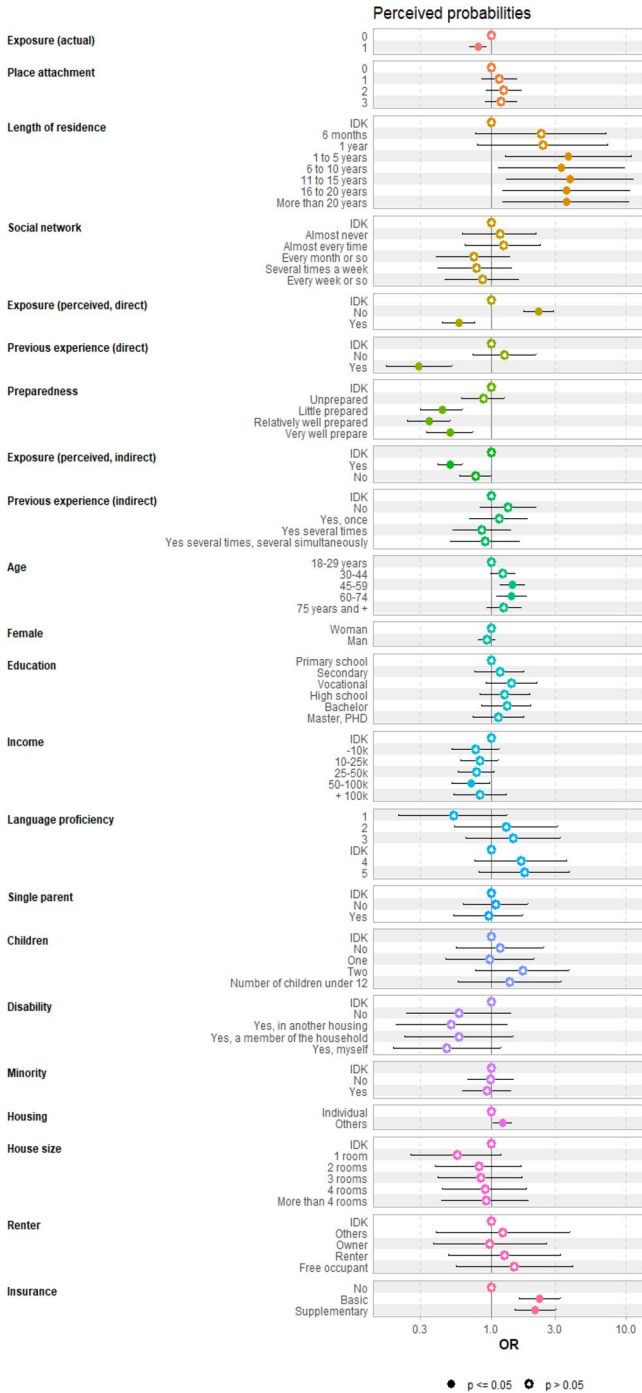


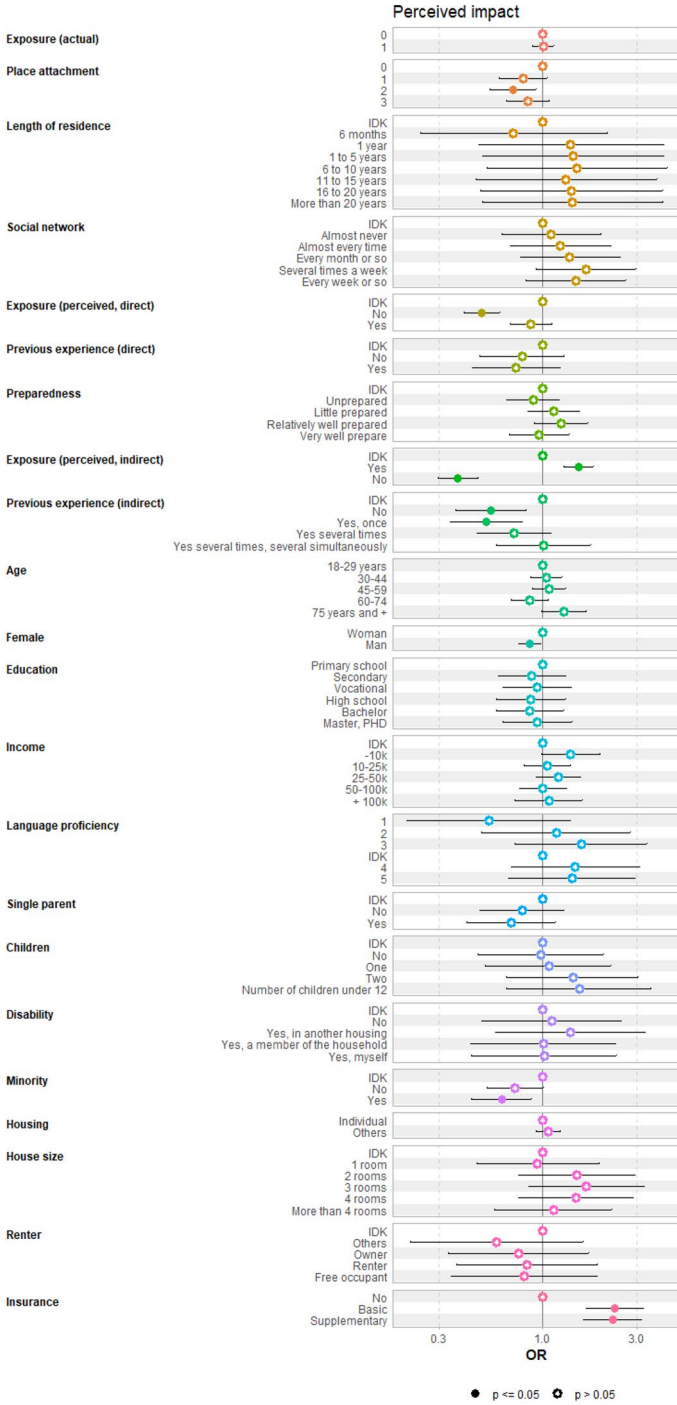
# HoP.

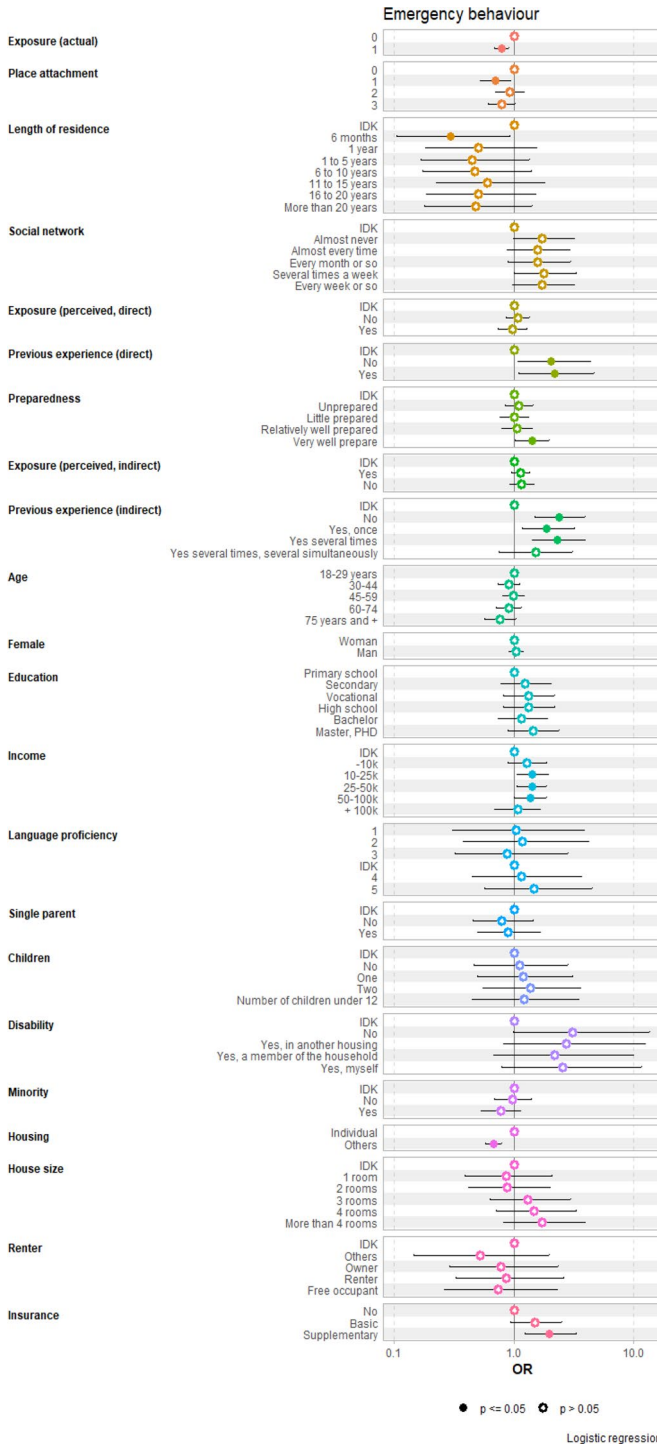
## HoP

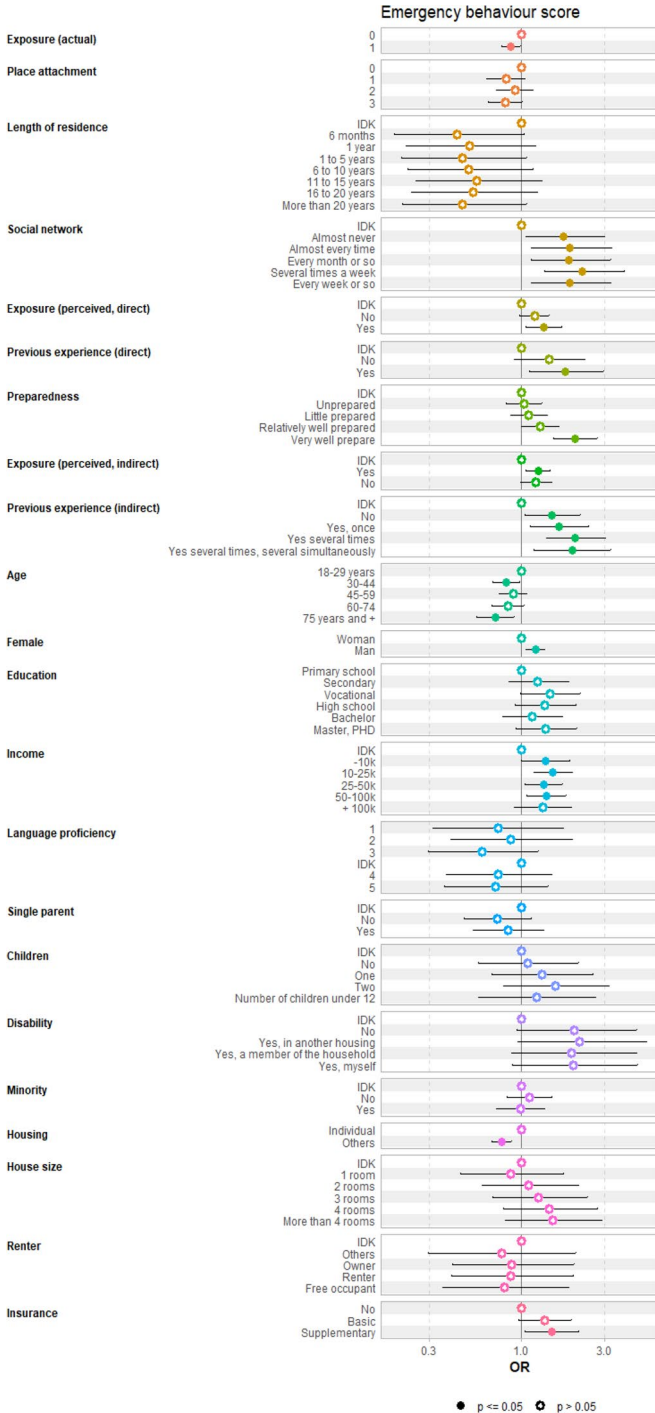


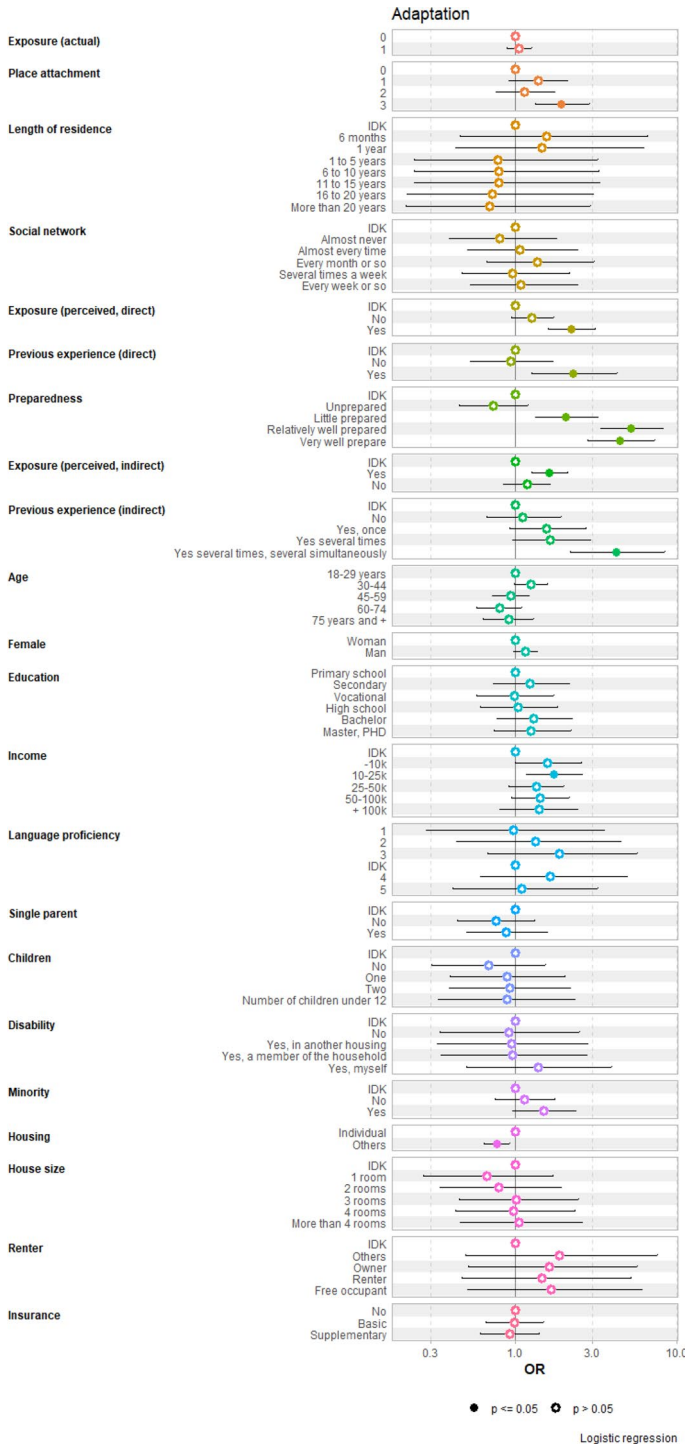
thresholds : Much less exposed|A little less -0.9225 A little less|A little more 0.8762 A little more|Much more exposed 3.0526

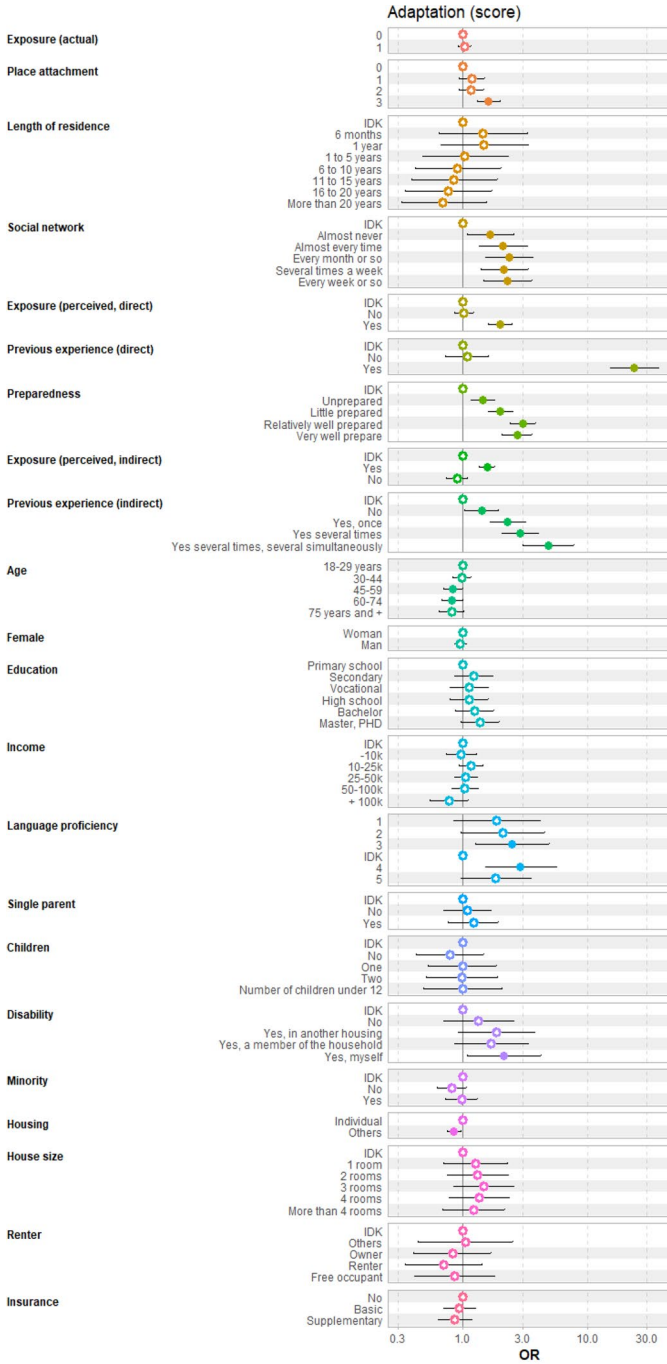








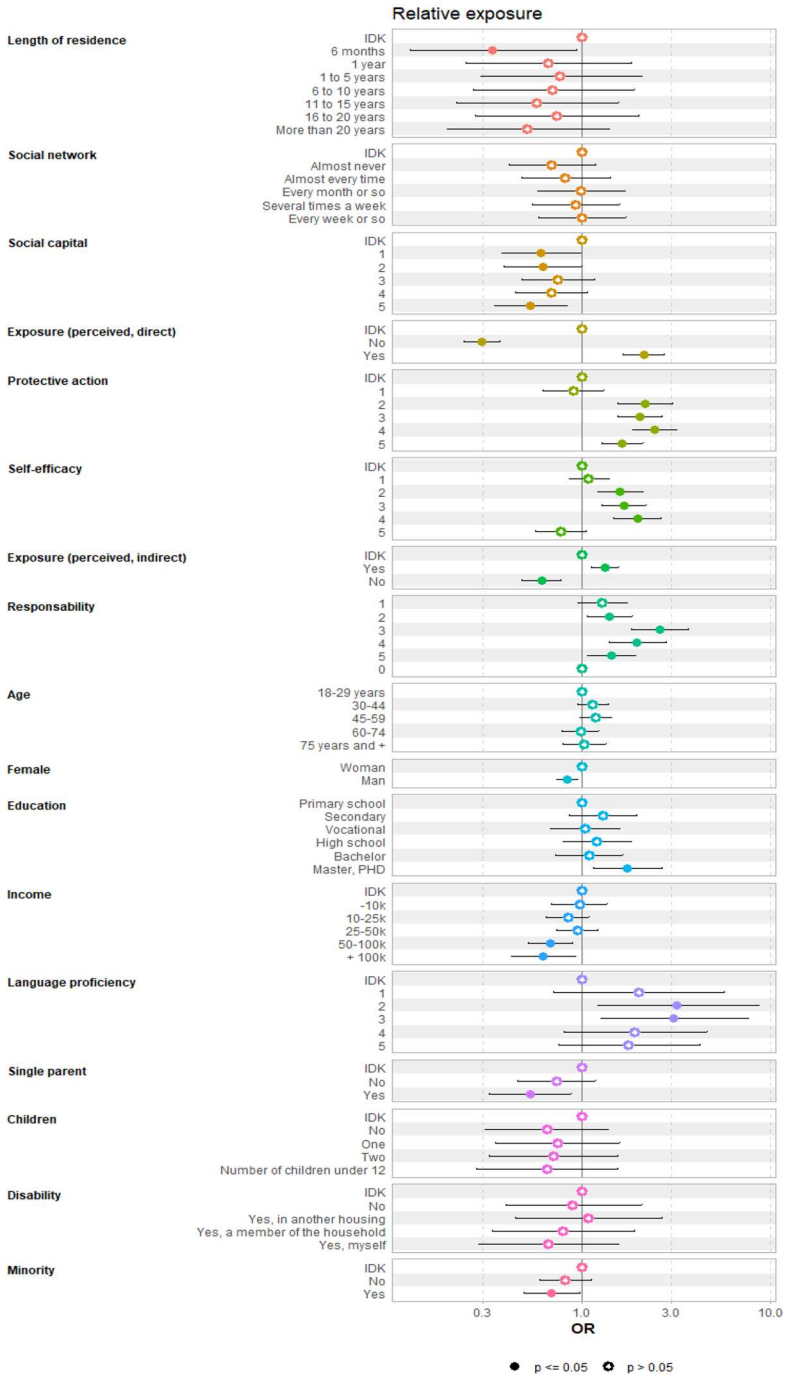


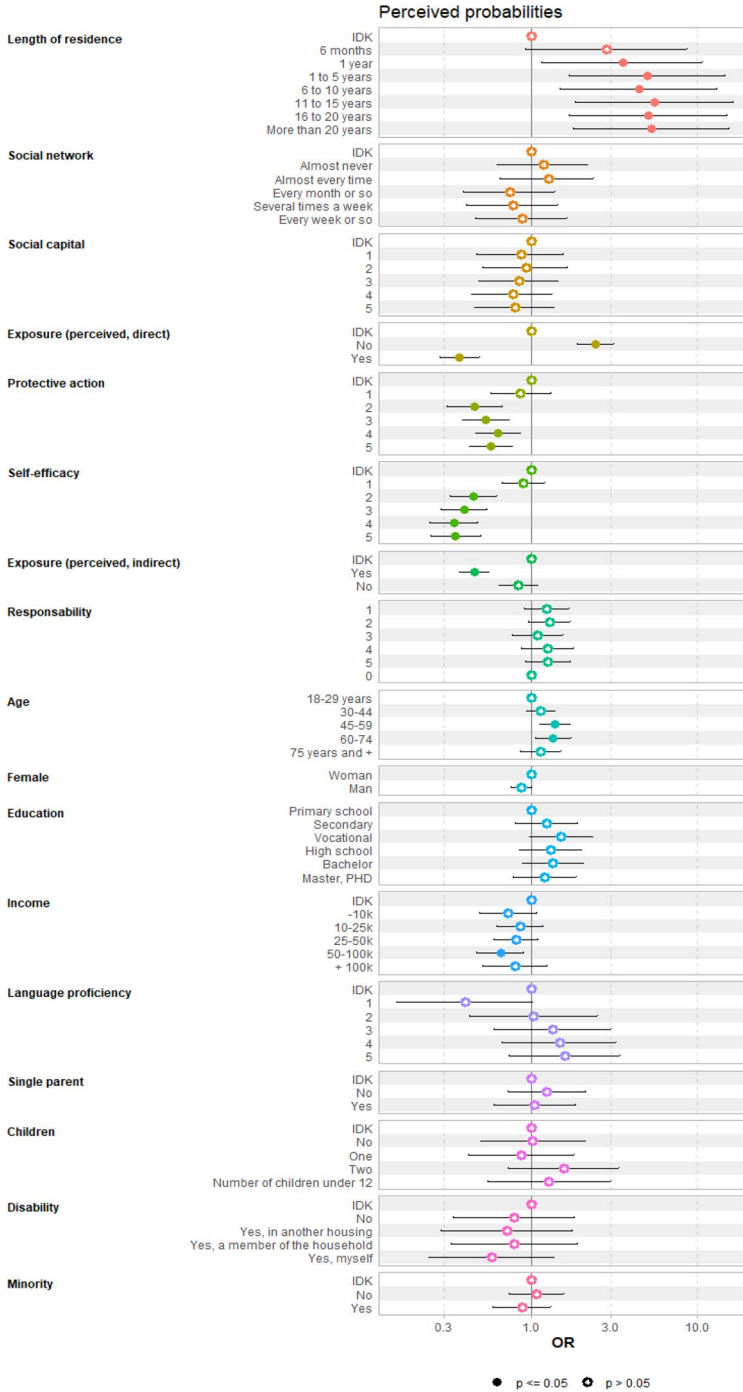


● p <= 0.05 ○ p > 0.05  
 thresholds : 0|1 2.4762 1|2 5.4919 2|3 7.8874 3|4 9.5639 4|5 11.1694 5|6 13.3439

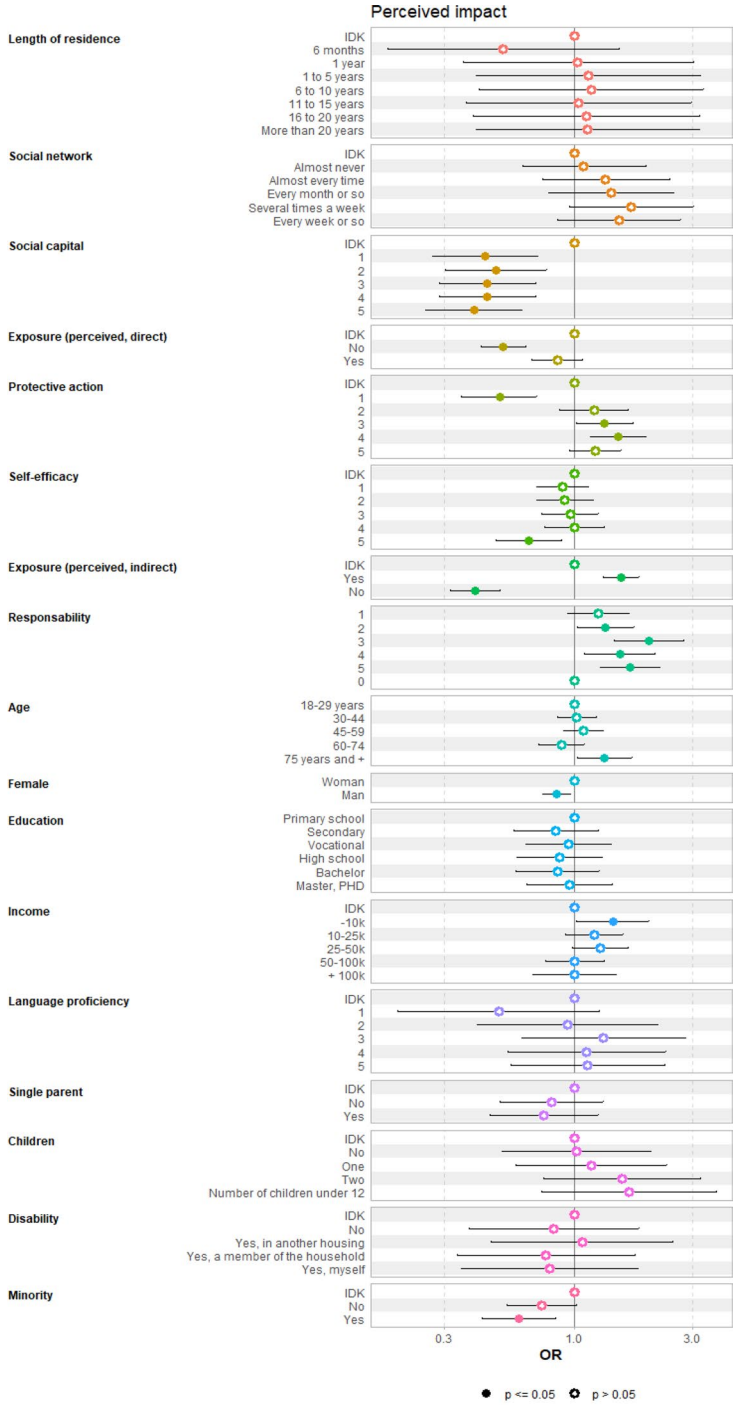
SCT

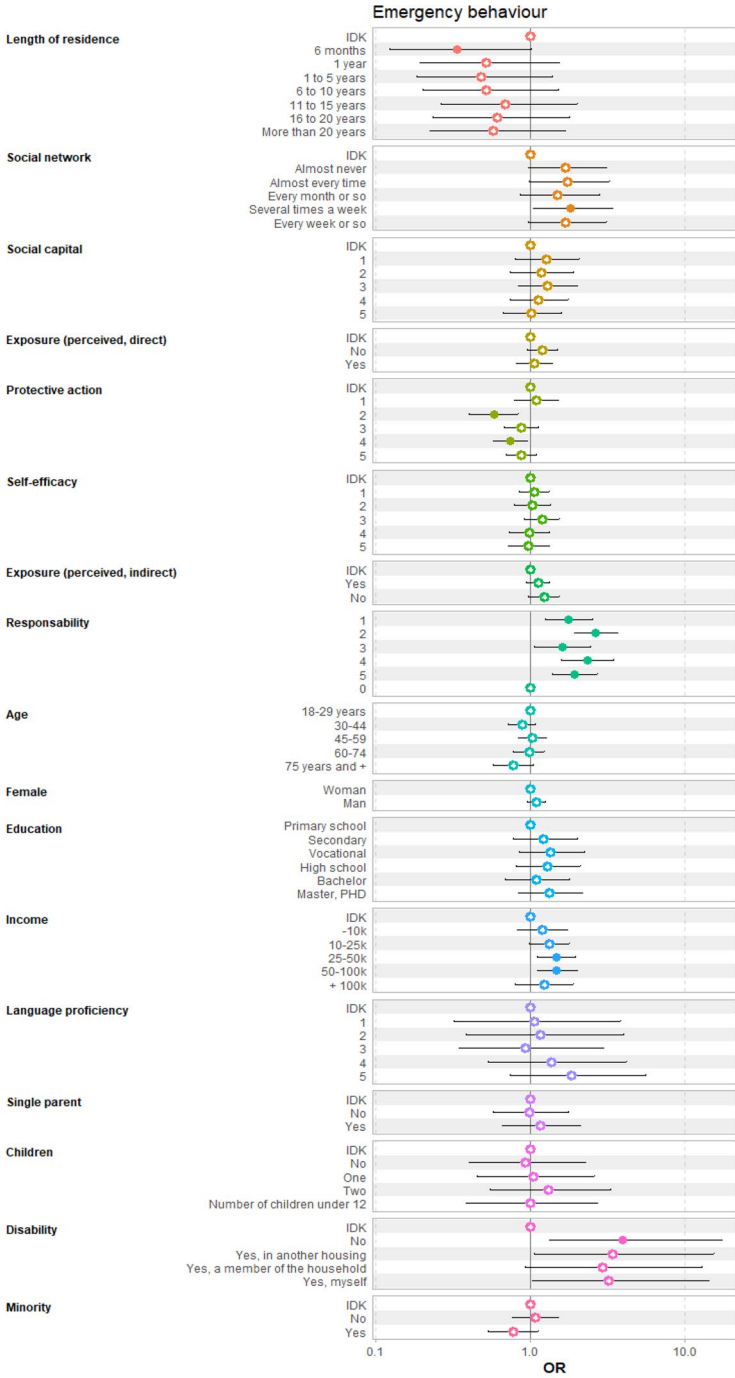
SCT





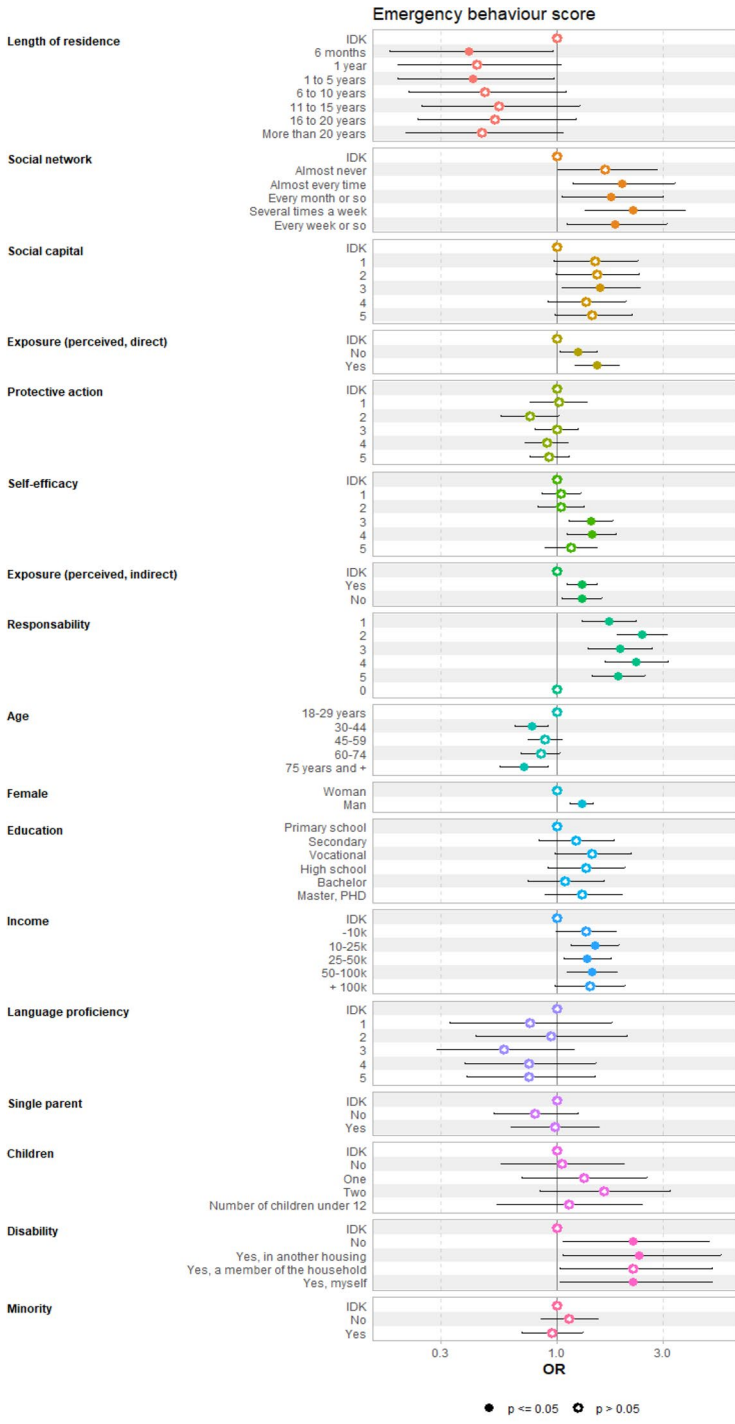
thresholds : Every year|Every 5 years|-2.3494 Every 5 years|10 years|-0.7959 10 years|30 years|-0.2001 30 years|50 years|0.0712 50 years|100 years and more|0.2724 100 years and more|Never|0.6973

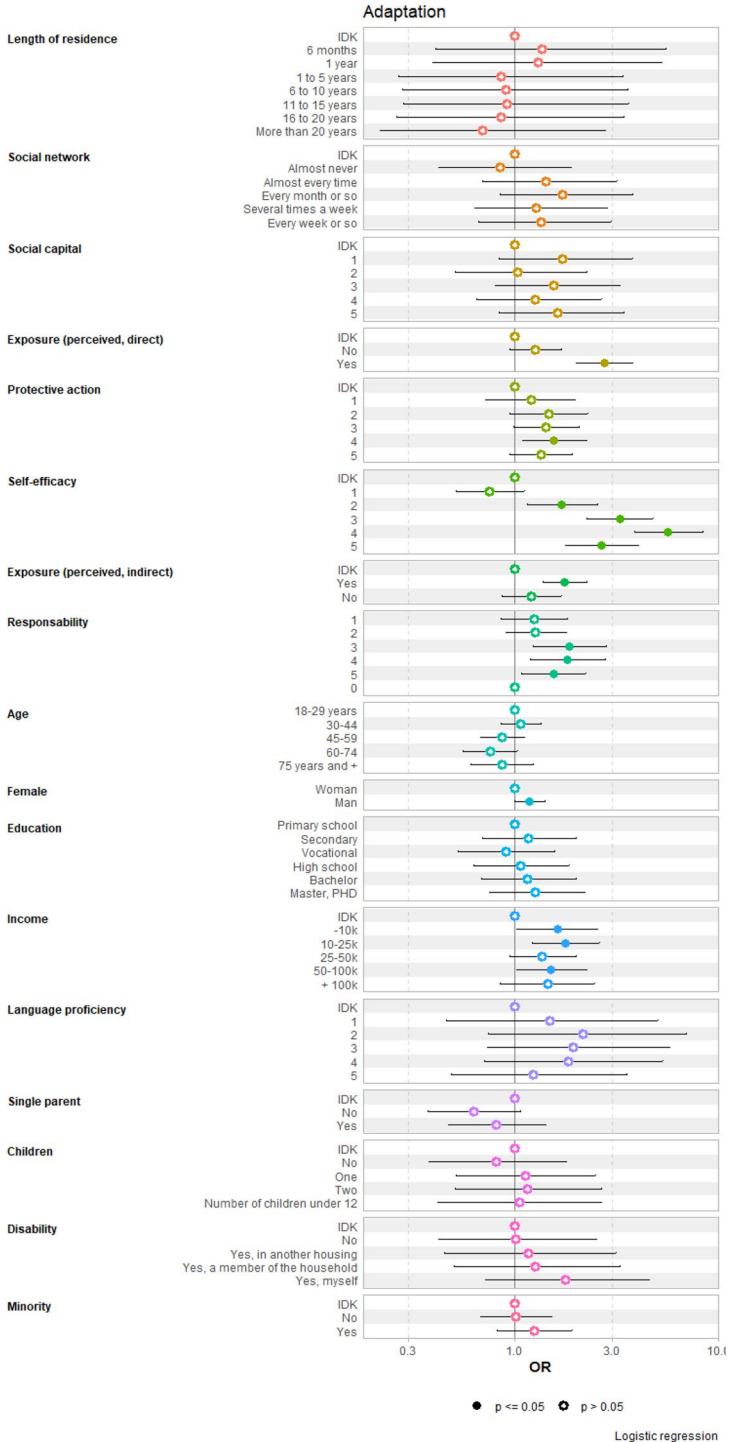


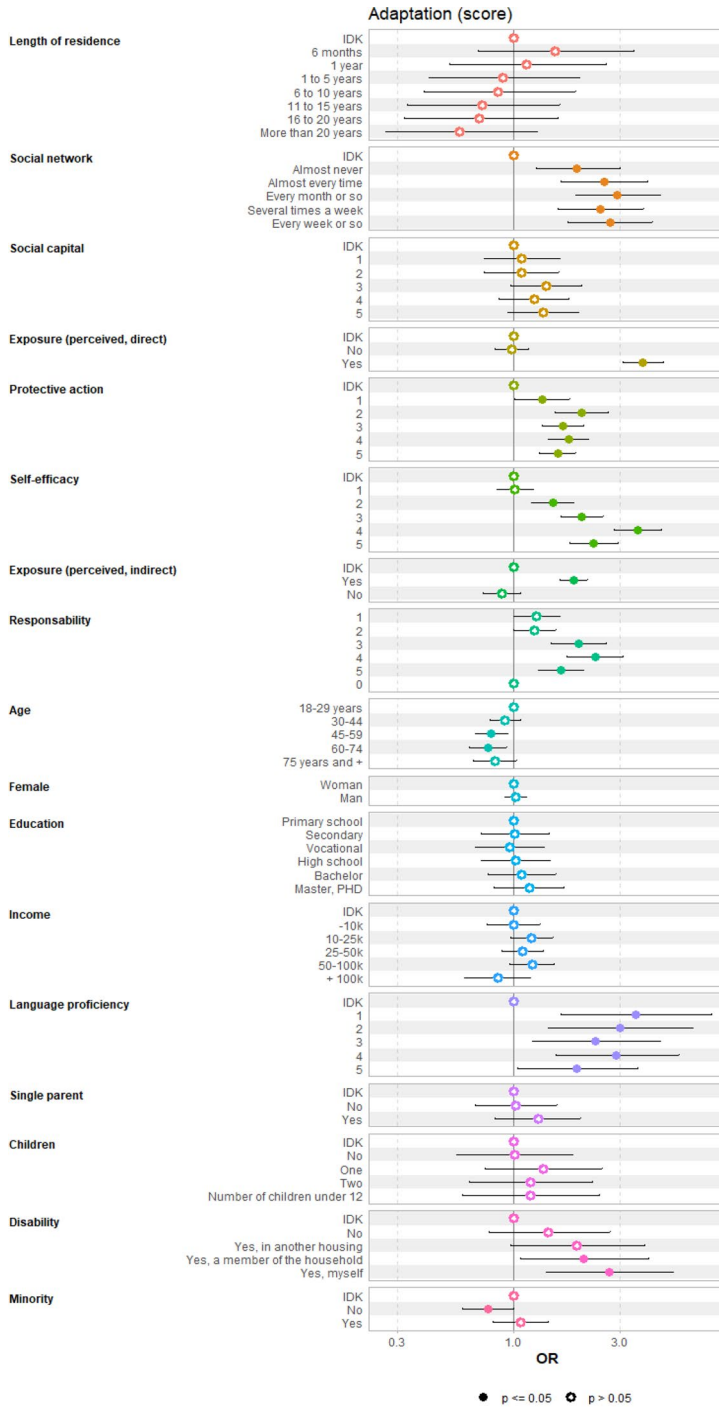


● p <= 0.05 ○ p > 0.05

Logistic regression



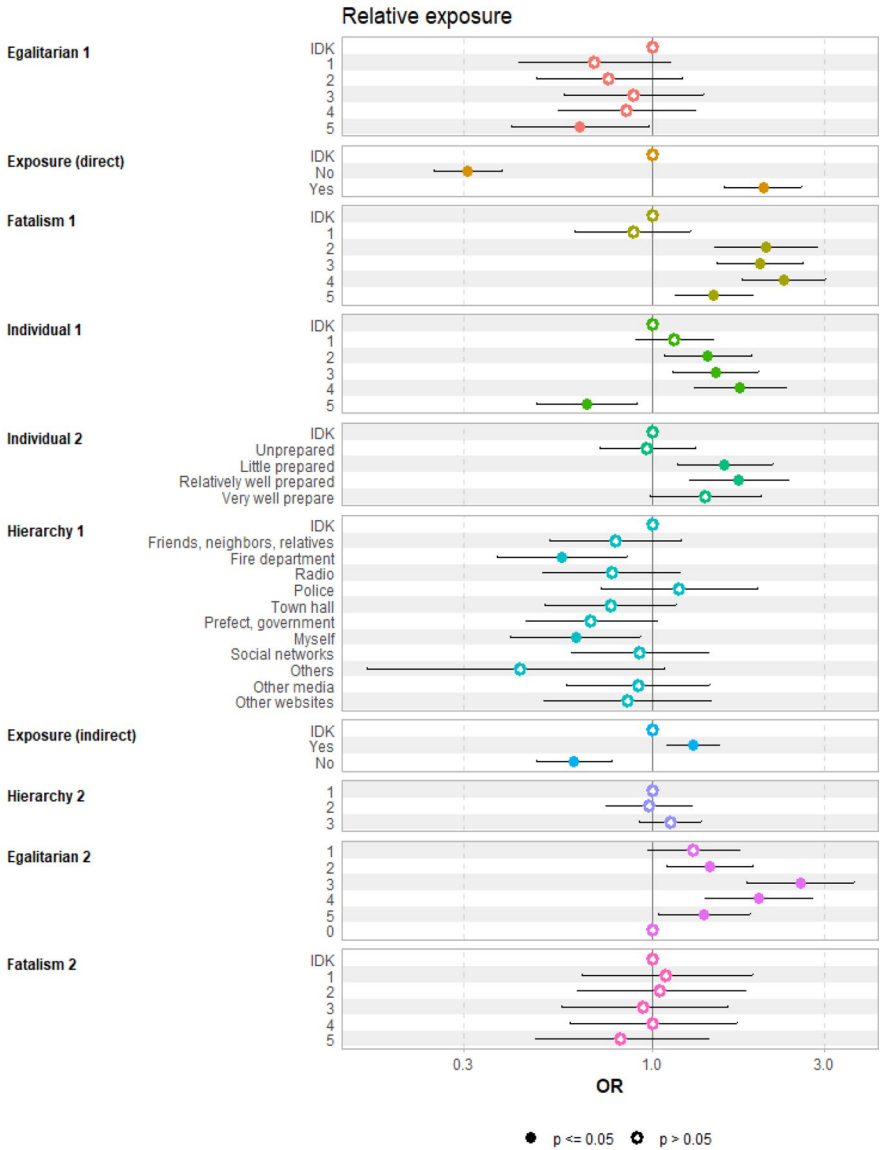




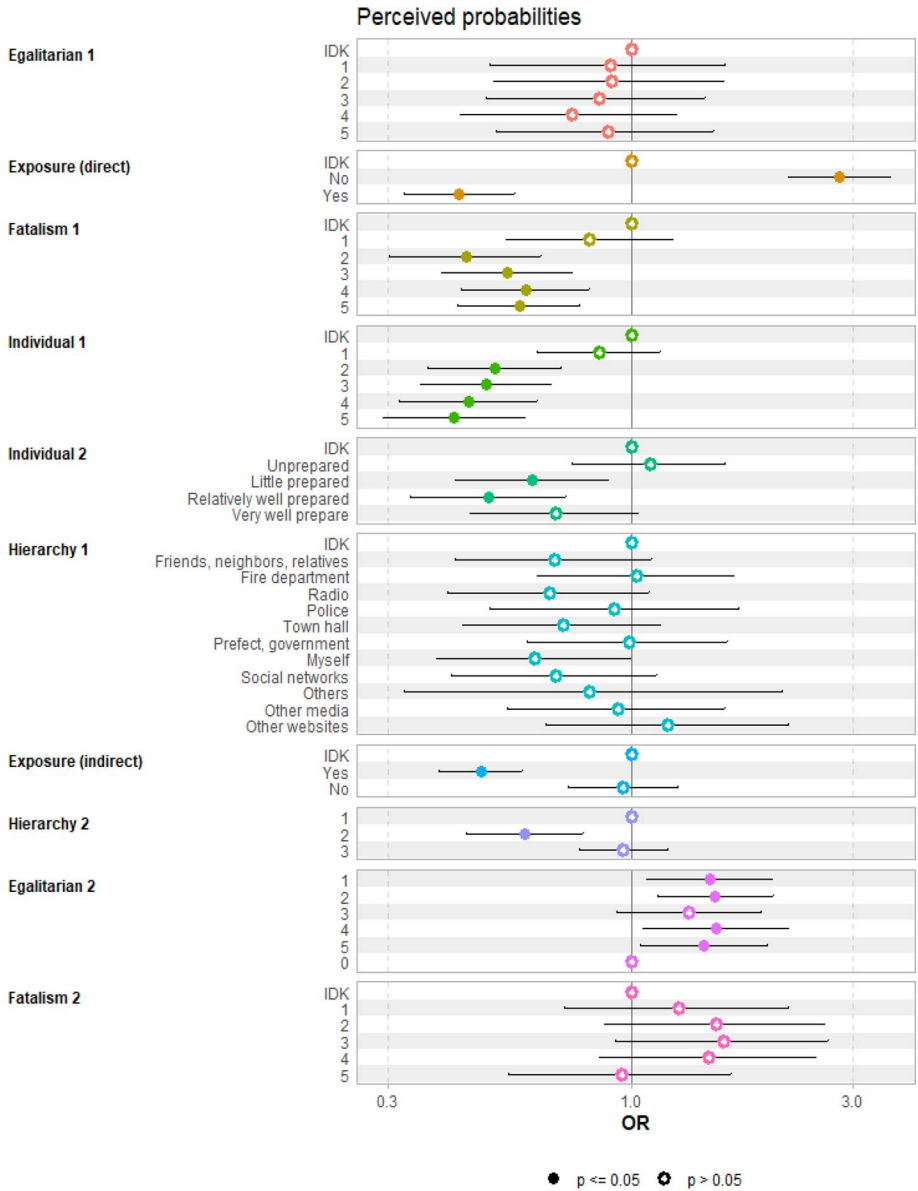
thresholds : 0| 1 2.6828 1|2 5.43 2|3 7.0839 3|4 8.3978 4|5 9.9038 5|6 12.0544

CTR

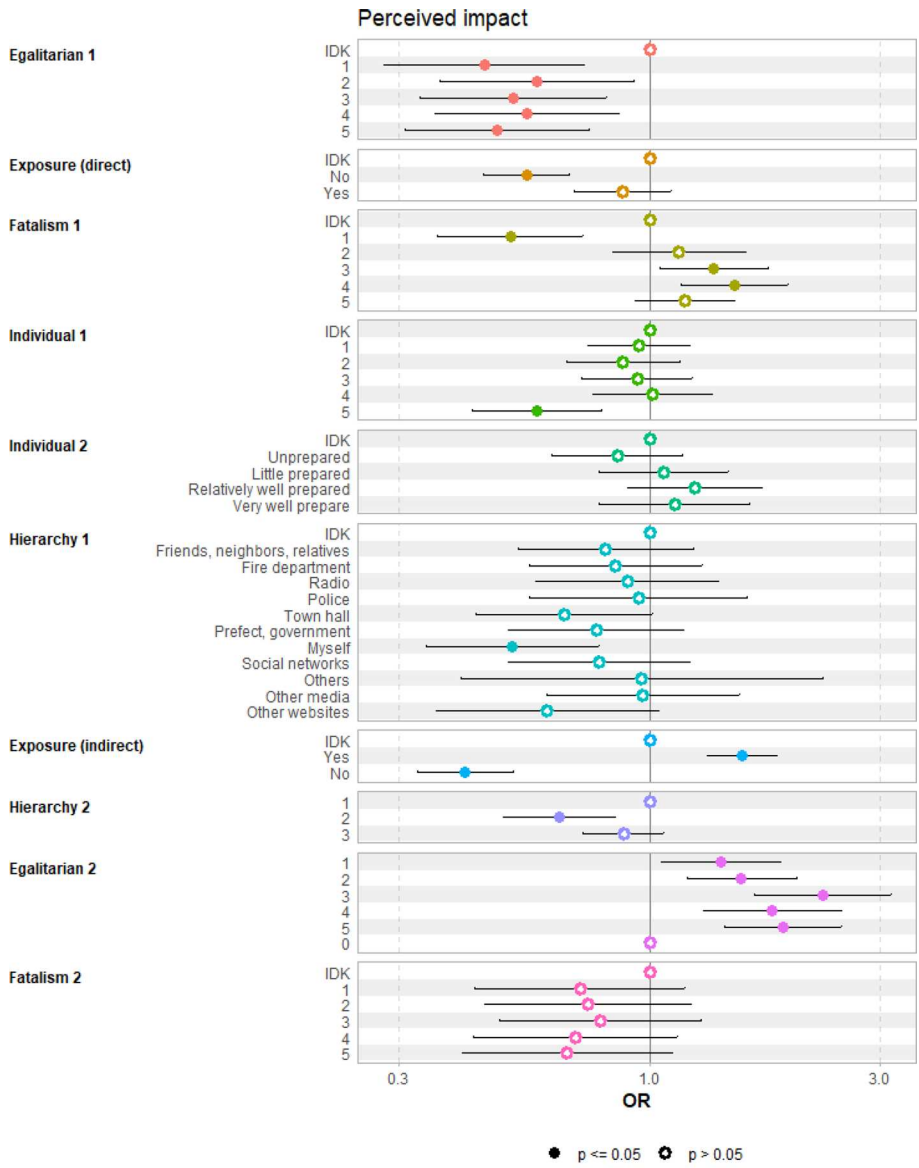
CTR



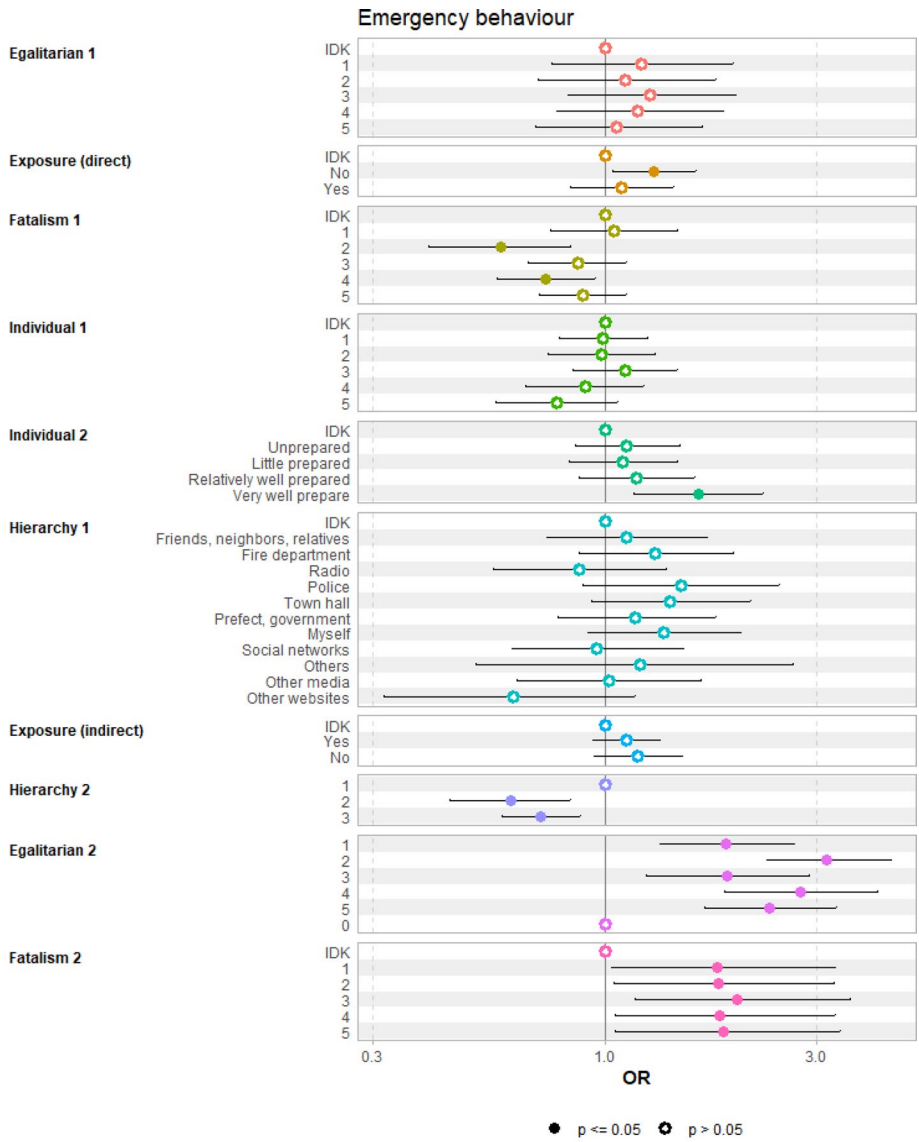
thresholds : Much less exposed|A little less 0.0597 |A little less|A little more 1.8042 |A little more|Much more exposed 3.8735



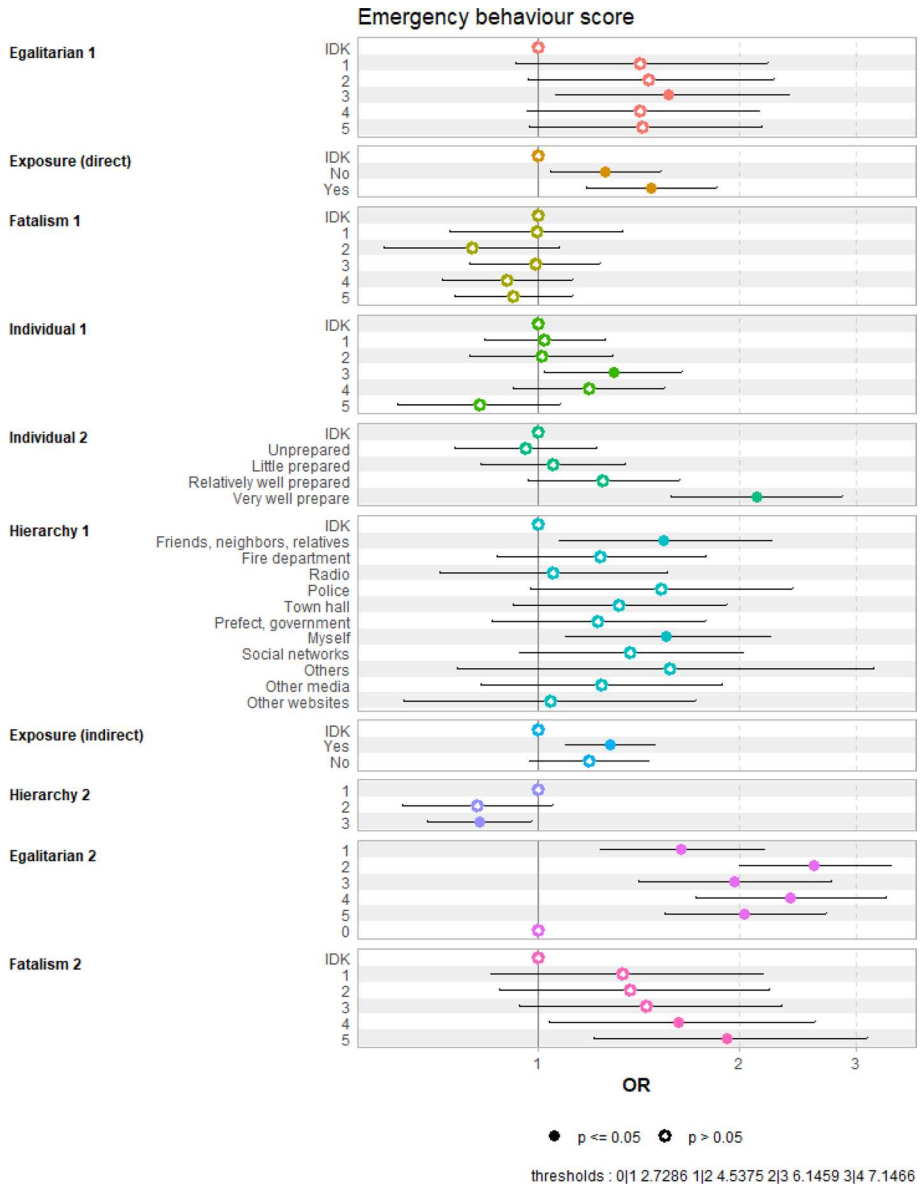
thresholds : Every year|Every 5 years|-4.284 Every 5 years|10 years  
 -2.7491 10 years|30 years|-2.1559 30 years|50 years|-1.8852 50  
 years|100 years and more|-1.6835 100 years and more|Never|-1.2599

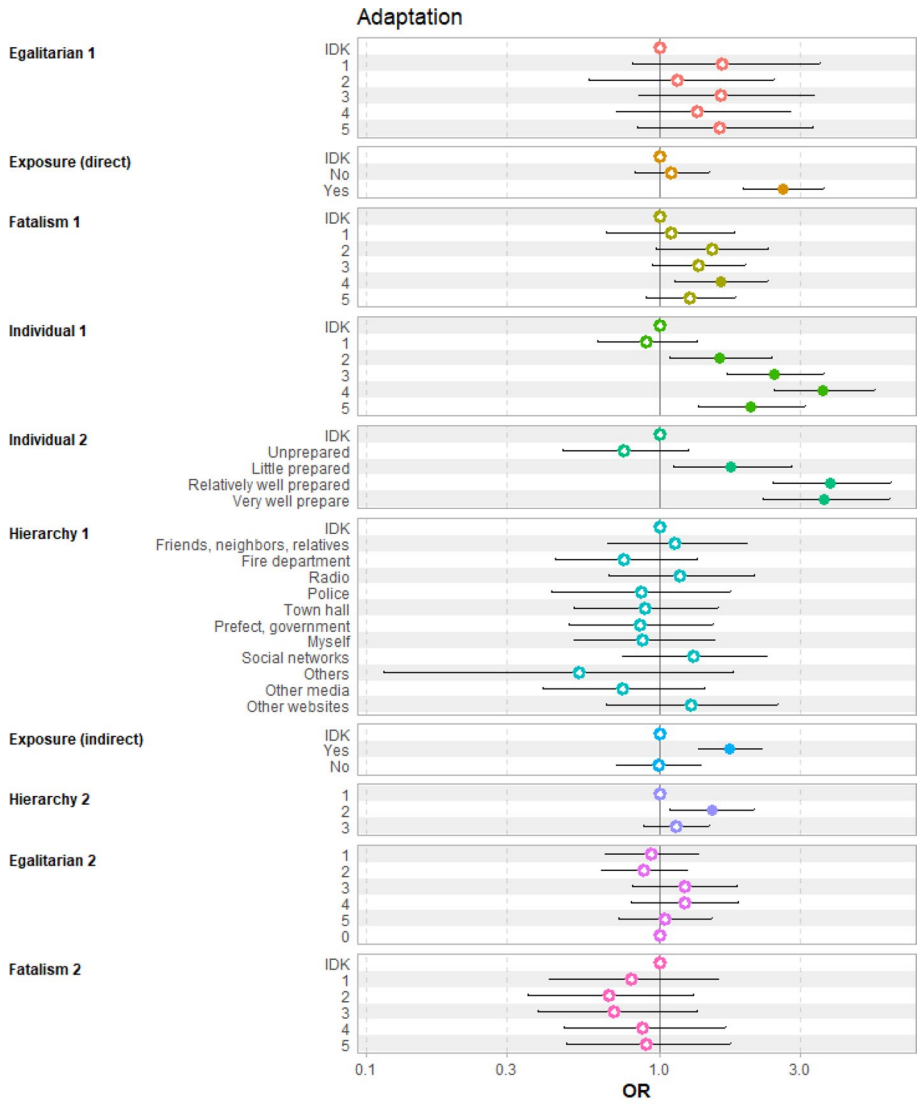


thresholds : Not serious|Not very serious -2.0767 Not very serious|Rather serious -0.5109 Rather serious|Very serious 1.6524



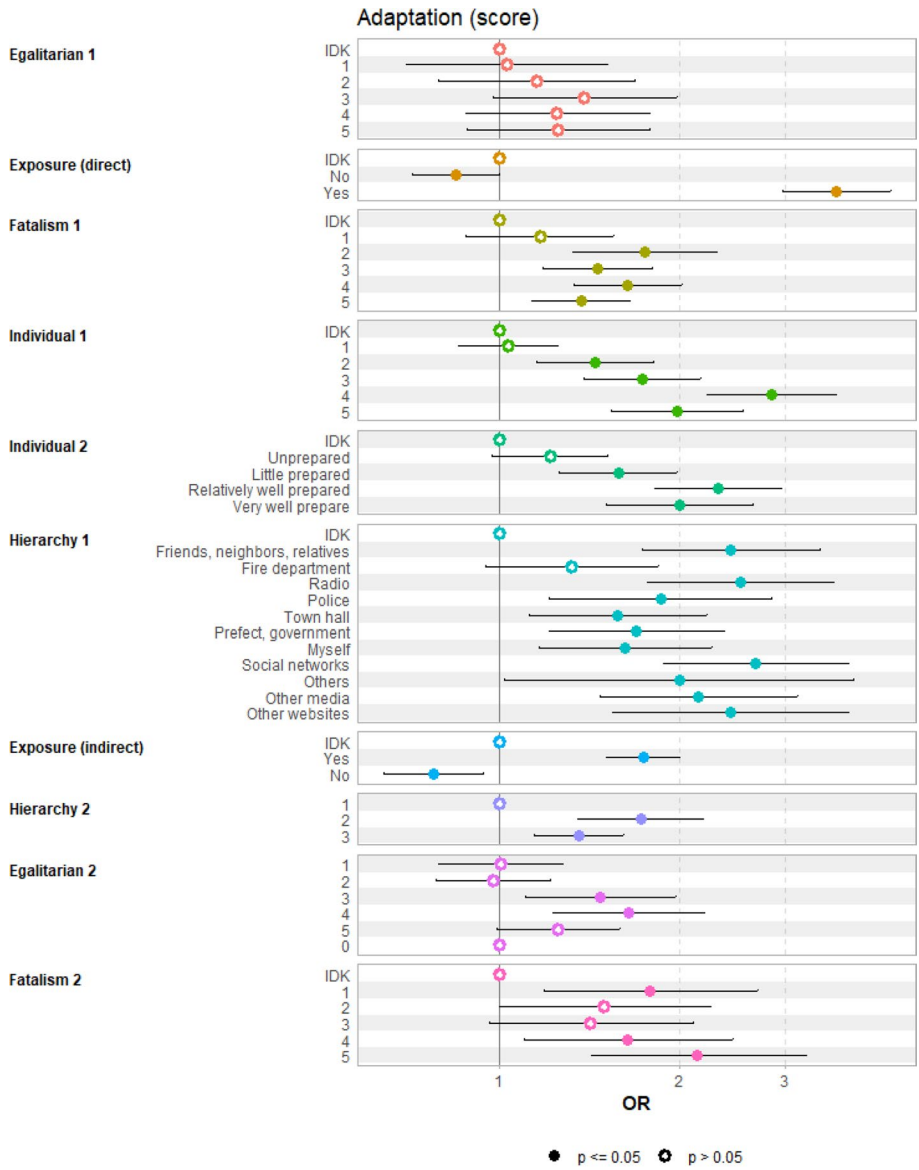
Logistic regression





● p <= 0.05    ○ p > 0.05

Logistic regression



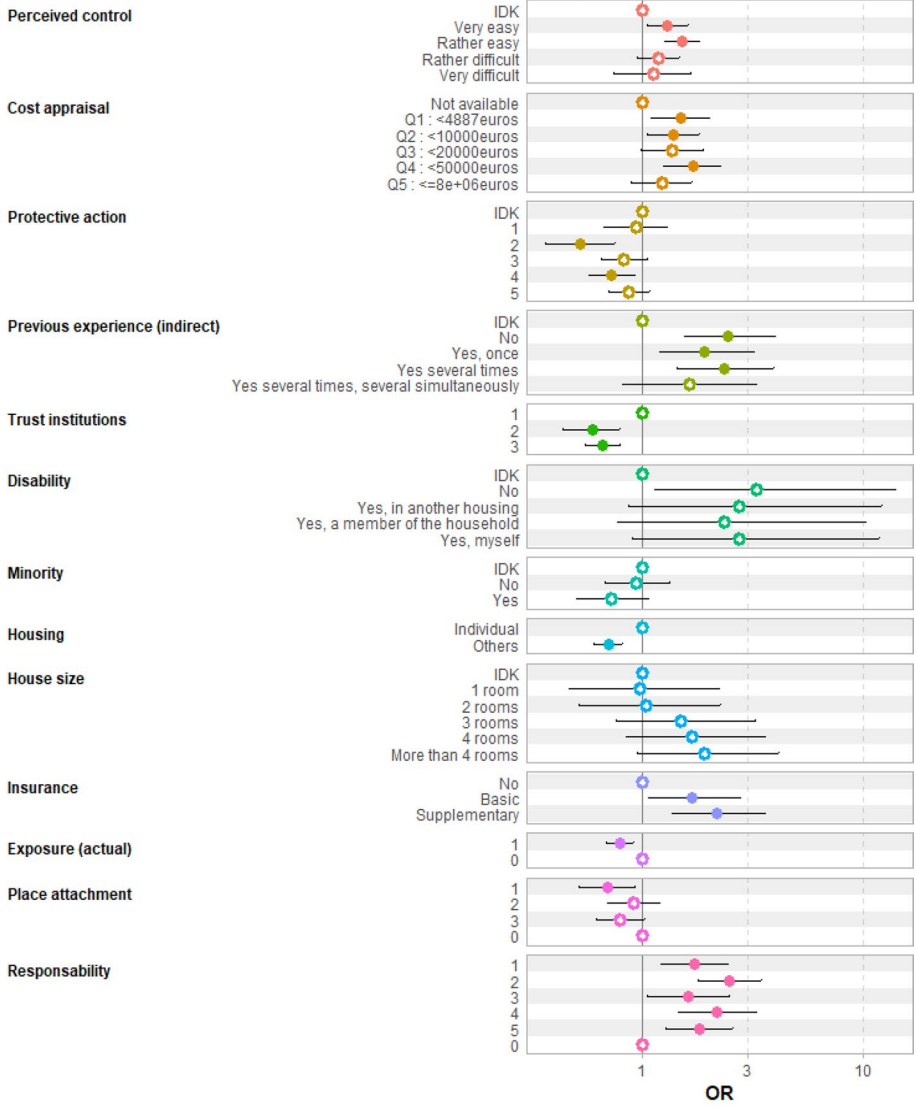
thresholds : 0|1 2.1629 1|2 4.8712 2|3 6.4854 3|4 7.7843 4|5 9.2901  
5|6 11.4391

# All combined.

All combined



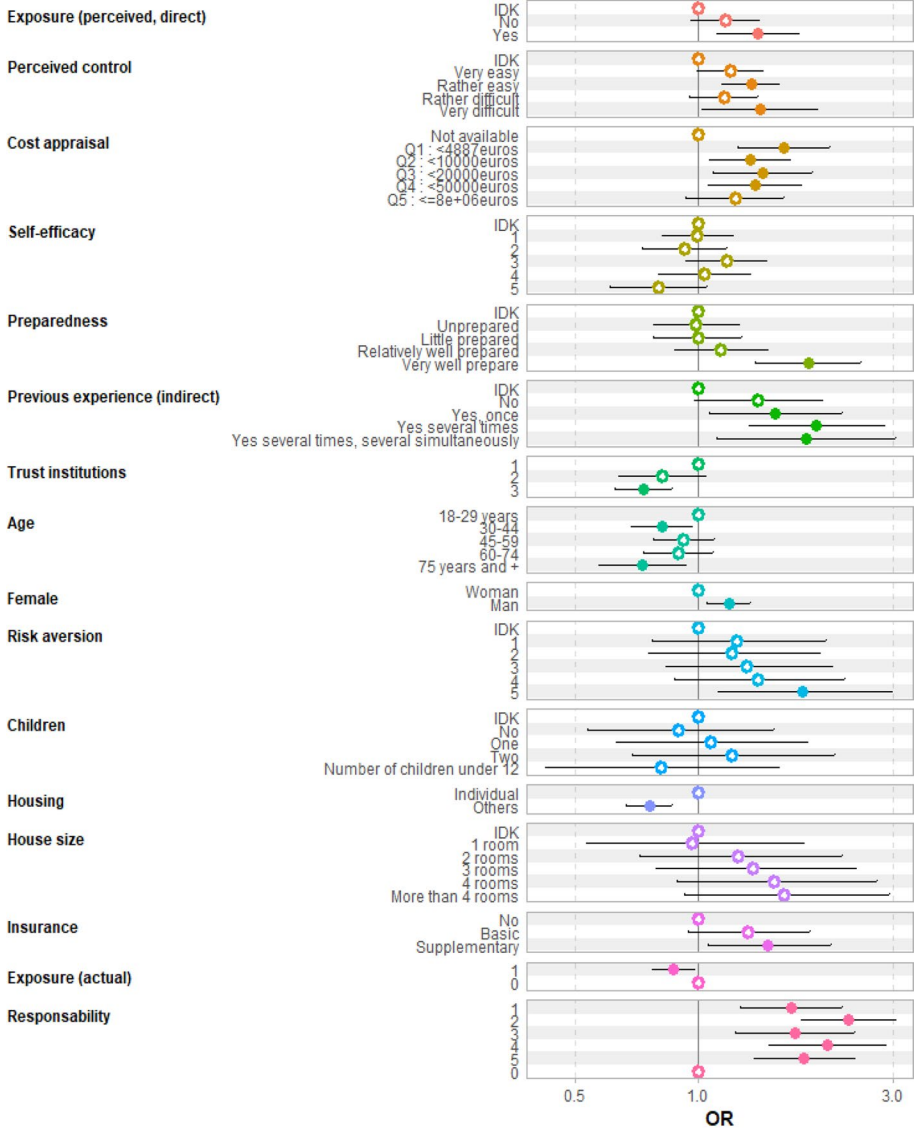
Emergency behaviour



● p <= 0.05 ○ p > 0.05

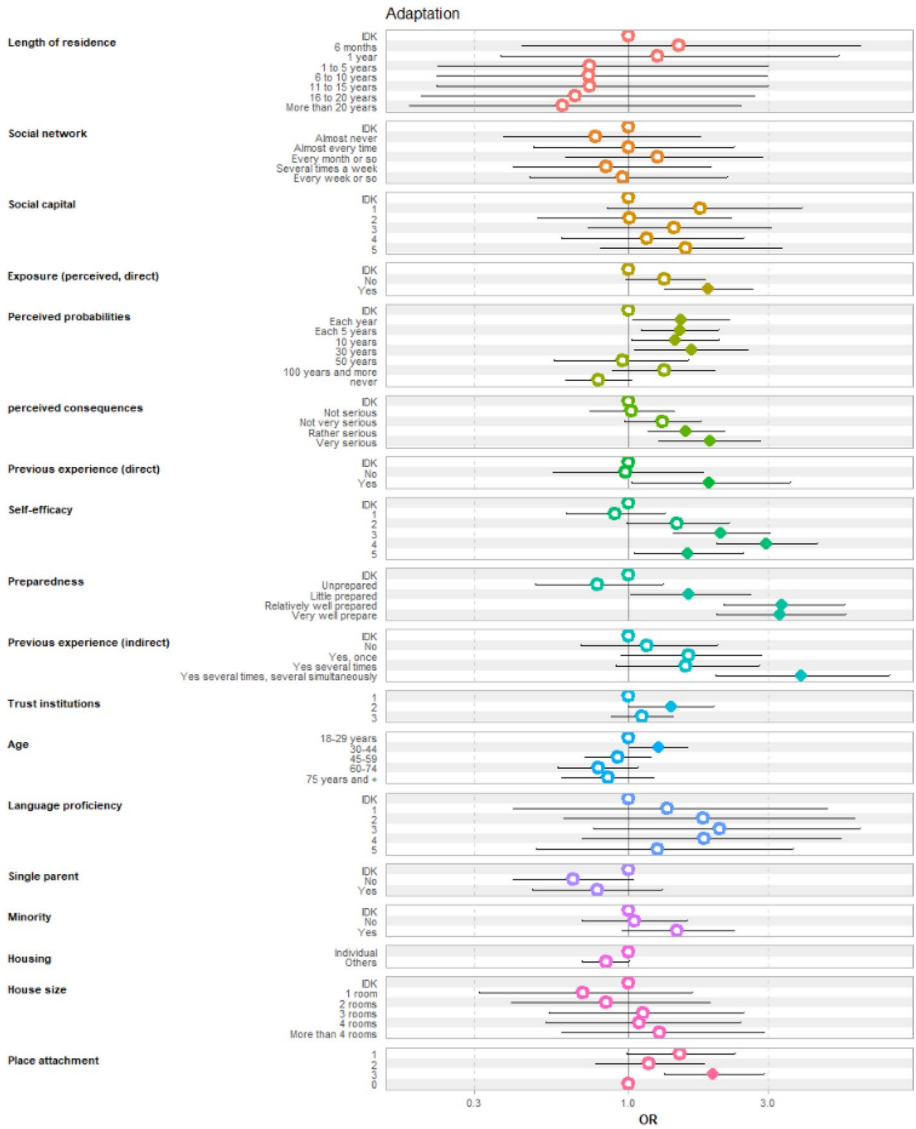
Logistic regression

### Emergency behaviour score



●  $p \leq 0.05$  ⚙  $p > 0.05$

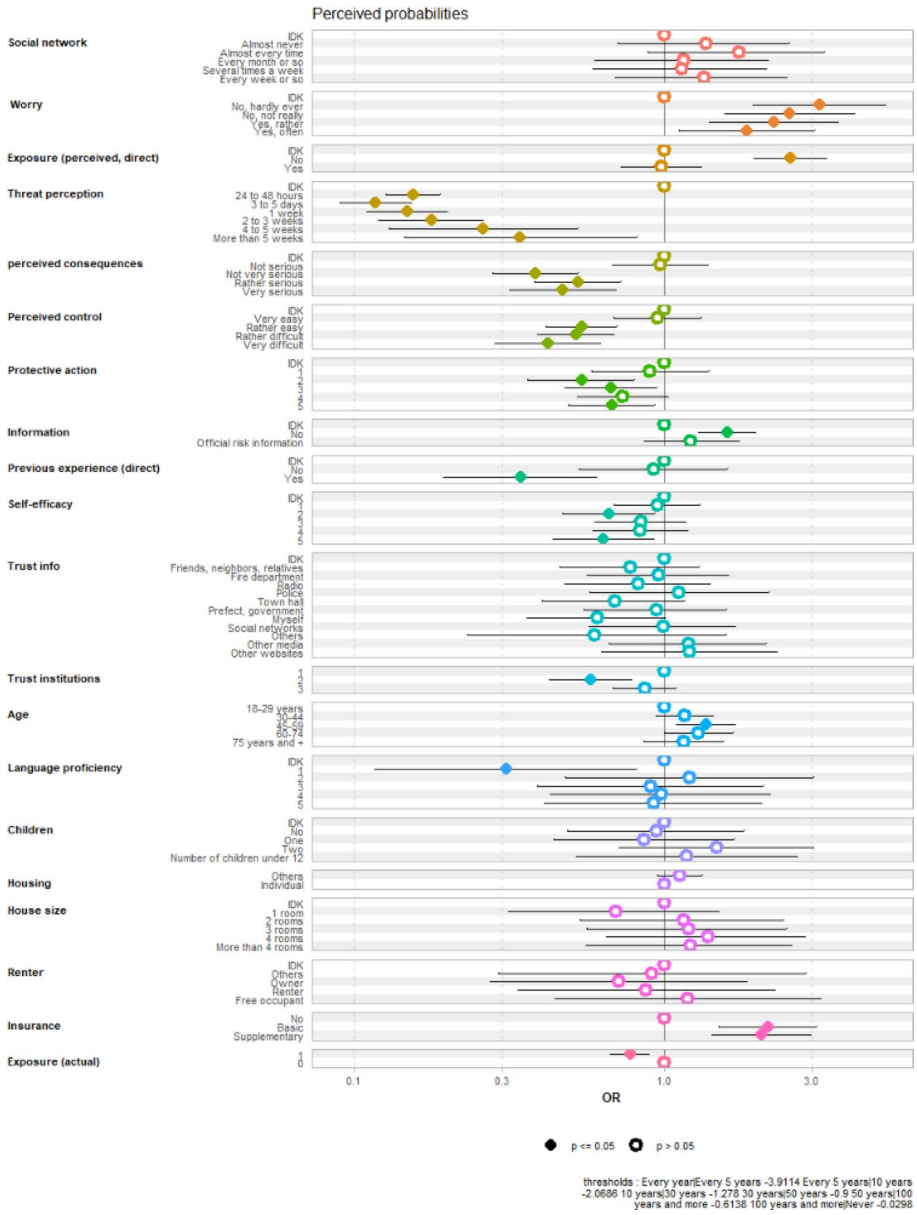
thresholds : 0|1 2.5095 1|2 4.3534 2|3 5.9709 3|4 6.9731

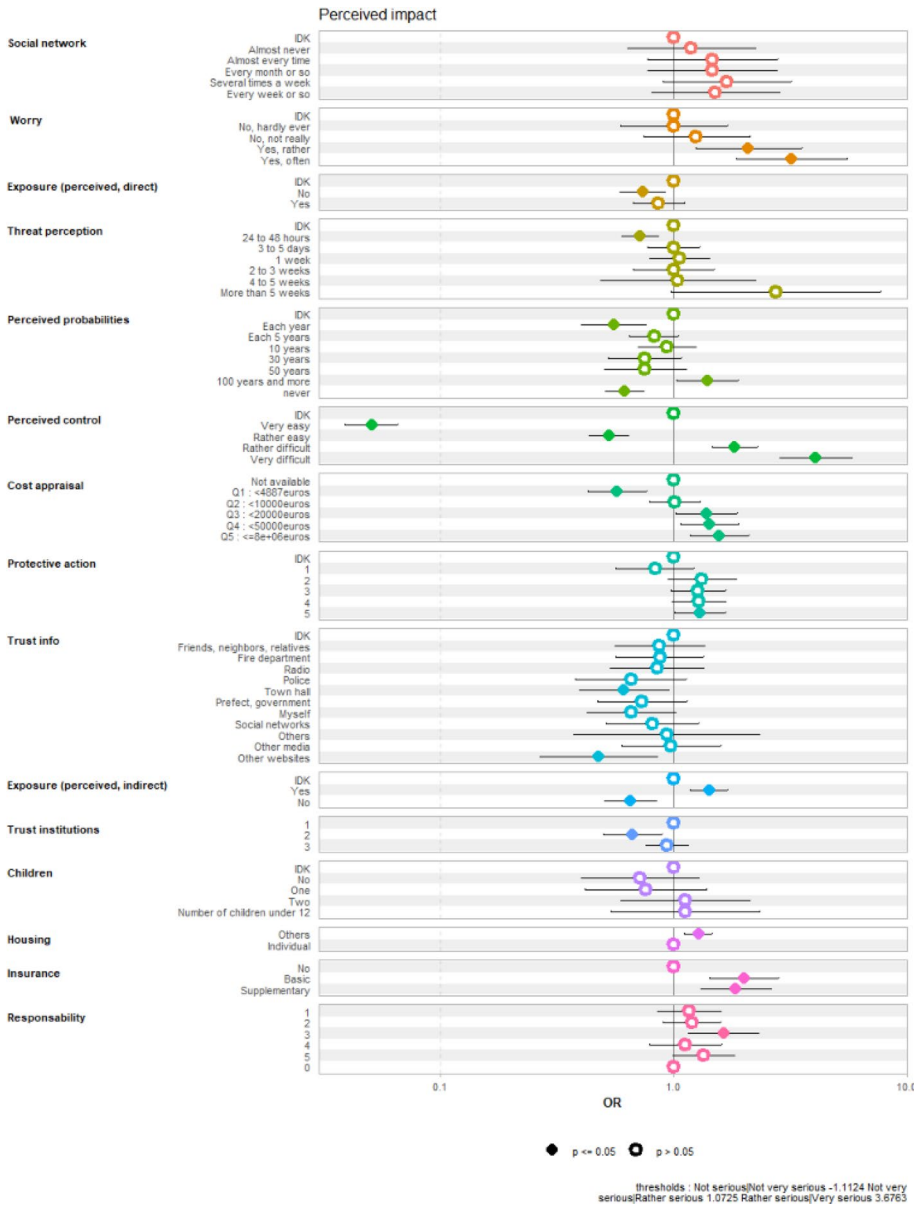


● p <= 0.05 ○ p > 0.05

Logistic regression







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## Declarations

**Conflict of interest** The authors have no relevant financial or non-financial interests to disclose.

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