

Addressing the social vulnerability gap in disaster risk perception

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ABSTRACT

While practitioners are often prompt to call for more risk communication campaigns, the impacts of disadvantage and vulnerability are often overlooked. This is related to social vulnerability frameworks that often fail to explicitly address risk perception, whereas risk perception theories usually overlook social vulnerability. The resulting social vulnerability research gap might be self-reinforcing: empirical studies will find it difficult to derive vulnerability as relevant for perception from the current theories, while the fragmented empirical evidence thus far offers little support to connect risk perception theories and social vulnerability frameworks. This study addresses this gap by exploring the links between social vulnerability and risk perception, first in the most commonly used theoretical frameworks – including adaptive behaviour, then with original empirical data from France after a series of floods ($n = 5,000$). The novelty is to compare the explanatory power of social vulnerability with two common explanations of risk perception: previous hazard experience and risk information. The models implementing social vulnerability are overall explaining the larger effects. Furthermore, when taking social vulnerability into account, experience remains a robust explanation, whereas information and campaigns often lose their significance. One key implication is that policies aimed at reducing social vulnerability might be more effective than risk communication campaigns to increase awareness and preparedness. This underlines the necessity to systematically investigate the impacts of social vulnerability on risk perception in a larger variety of case studies, disaster stages, and hazard types.

1. Introduction

Despite decades of research on protective behaviour and risk perception, the impacts of disadvantage and vulnerability are often overlooked [1], especially in materially advantaged societies [81]. Highly exposed and vulnerable people often feel left alone to cope with and adapt to the consequences of flooding [2], and even the most adapted and experienced groups feel helpless after repeated disasters [3]. While individual capacity and resources to reduce losses caused by extreme events are highly influenced by individual knowledge, resources and power to undertake active actions [78], understanding why households can neither afford nor are willing to engage themselves in such actions requires disaggregating population groups and socially vulnerable situations [44]. However,

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disaster risk reduction (DRR) and climate change adaptation (CCA) thinking and policy are increasingly fostering public engagement, individual awareness and individual responsibility, emphasising individual perception and behaviour. Limits on individual action and the impact of social vulnerability remain too often unquestioned. As a result, many studies might conflate the lack of capacity with a lack of knowledge or willingness [4]. What the literature calls “risk denial” or “lack of risk awareness” might be a rational defence mechanism if some groups cannot escape hazard exposure and are in too vulnerable situations to adapt [5,82].

Disentangling the connections of risk perception with the underlying social vulnerability and exposure remains a challenge [6,7]. Uncertainty derives from both theoretical and methodological challenges. A recent meta-analysis has found that theories focusing on individual perception, decision-making processes and behavioural aspects prevail in the fields of DRR and CCA. In contrast, theories shedding light on collective social processes and social vulnerability have a low uptake [8]. This means social processes are

Table 1

Theories with a focus on risk perception, implementing vulnerability or adaptation.

Theory	Focus on risk perception	Contains the term ‘vulnerability’	Contains the term ‘adaptation’
Construal Level Theory (CLT)	CLT explains that risk perception and decision-making vary according to several type of distance, temporal, spatial, social and hypothetical (likelihood) distances. Proximity is associated with low-level construal, when people think more concretely and focus on the near future, making people less likely to engage in risky behaviour or to procrastinate.	No, but social capital is mentioned	no
Cultural Theory of Risk (CTR)	CTR asserts that social organizations endow individuals with perceptions that reinforce those structures in competition against each other. Attitudinal scales reflect the “worldviews” associated with organisation constraints and ways of life. Risk perceptions are distributed across persons in patterns better explained by culture and power than by other potential influences.	No, but inequalities are mentioned	no
Expected Utility Theory (EUT)	EUT explains which option rational individuals should choose in a complex situation, based on their risk aversion and preferences. Agents choose between prospects by comparing utility values: the sum of the payoffs multiplied by their probabilities. It has been invalidated in experiments.	no	no
Person Relative to Event (PrE)	PrE emphasizes the relationship between level of appraised threat, resources and fear. While increasing levels of threat when resources are appraised as insufficient will be fear-arousing and decrease problem-focused coping, appraising resources as sufficient in quantity and quality to minimize the negative consequences will increase levels of preparedness.	no	no
Prospect Theory (PT)	PT describes how individuals assess their loss and gain perspectives in an asymmetric manner (loss aversion). Humans do not undertake a full cost-benefit analysis to determine the optimal decision, but choose an option that fulfils their criteria (bounded rationality).	no	no
Protection Motivation Theory (PMT)	The risk appraisal process consists of the perceived probability and the perceived severity of the events. The coping appraisal process depends on a person’s belief in his own ability to carry out the adaptation measure (perceived self-efficacy), the belief in the effectiveness of the adaptation measure (perceived response efficiency) and the perceived costs of the adaptation measure.	no	yes
Protective Action Decision Model (PADM)	PADM identifies three core perceptions (threat, protective action, social and environmental cues) that form the basis for comprehension of warnings or exposure and decisions about how to respond to an imminent or long-term threat.	No, but in some applications, social capital and perceived inequalities are explored	yes
Psychometric Paradigm (PP)	PP focuses on the roles of affect, emotion, and intuition in influencing risk perception by examining expressed preference: the degree to which a risk is understood, the degree to which it evokes a feeling of dread, the number of people exposed to the risk. A dread risk produces feelings of terror, worry, inequality, and uncontrolled. An unknown risk is new. The more a person dreads an activity, the higher its perceived risk and the more that person wants the risk reduced.	No, but inequalities are mentioned	no
Social Amplification of Risk Framework (SARF)	Certain aspects of hazard events and their portrayal in mediated and other sources interact with psychological, social, institutional, and cultural processes in ways that might attenuate (decrease) or amplify (increase) perceptions of risk and, through this, shape behaviour.	No, perceived inequality of risk distribution is sometimes mentioned but this is exposure	no
Theory of Planned Behaviour (TPB)	TPB links beliefs to behaviour. The theory asserts that three core components, attitude, subjective norms, and perceived behavioural control, shape an individual’s behavioural intentions. In turn, behavioural intention is considered the most proximal determinant of human social behaviour.	no	yes

predominantly analysed and explained through the lens of individual actions and sense-making processes. The dominant methodological individualism also results in the exploration of isolated socio-demographic characteristics that impact risk perception and adaptive behaviour [9]. Socio-demographic characteristics are among the most contested drivers [10], even though some variables are usually collected to assess the survey sample compared to census data [11], they are inconsistently implemented and tested from one study to another [5,12]. Moreover, a few unsettled socio-demographic drivers studied in isolation might misrepresent the impact of social vulnerability [12], as intersectionality theory incorporates how multiple positions of disadvantage jointly affect vulnerability, intersectional groups to experience distinct disaster outcomes than individual populations [1].

While practitioners and first-responders are often prompt to call for more risk communication and awareness campaigns [13,14,67,72] or to suggest that at-risk people lack judgment or motivation [15], we argue that such claims are rarely thoroughly investigated (e.g., [12,16,17]), whereas studies usually overlook the social vulnerability and capacities of the most exposed people. Our general assumption is that disadvantage and vulnerability are kept in a blind spot because risk perception theories and adaptive behaviour models are typically disconnected from social vulnerability frameworks. This results in a gap, both from the academic and practitioner perspectives. A follow-up research question would be to explore social vulnerability as an ancillary or alternative explanation of risk perception, compared to the most common assumptions – i.e., the impacts of previous hazard experience and the effectiveness of risk awareness campaigns. This study addresses this social vulnerability research gap by exploring the links between social vulnerability, risk perception, and adaptive behaviour, first in the most commonly used theories and frameworks; second, with empirical data from France after a series of floods; and third, it discusses the opportunity to update existing frameworks.

2. A social vulnerability research gap

Theoretical frameworks are intended to guide the research design, the selection of research questions and possible explanations. While there is a diversity of theoretical frameworks in the areas of risk perception, adaptation and vulnerability, hermeticity between these areas, compatibility among theories or interconnection issues might result in social vulnerability to be systematically overlooked in disaster risk perception studies, and vice-versa. In turn, if the lack of interconnectedness between relevant theories results in a blind spot, this might explain the fragmented empirical evidence published so far.

2.1. Theoretical frameworks

First, we investigate the main risk perception and adaptive behaviour theoretical frameworks to determine whether they include social vulnerability as a driver or factor. Then, we examine the main social vulnerability frameworks to investigate if they include risk perception or adaptive behaviour. A recent study found that disaster risk perception studies are not strongly embedded in a theoretical framework: despite some high-profile theories, their overall uptake and usage in empirical studies across hazards and context is lower than expected [12]. This issue is not specific to disaster risk perception or behaviour: a recent large meta-analysis on the role of theory in publications on social vulnerability, resilience, and adaptation found that 90 % of studies had no explicit theoretical underpinning [8]. We used this meta-analysis [8] and this recent survey among experts in the field [12] to establish a list of the main theories and frameworks, and we first investigated if the theories with a focus on risk perception are implementing vulnerability or adaptive behaviour (Table 1).

Table 1 indicates that none of the main theories on risk perception also considers social vulnerability and adaptive behaviour. In fact, no theory considers social vulnerability as a driver or factor, even if some applications of the Protective Action Decision Model (PADM) explore social capital or perceived inequalities in isolation [18]. Conversely, adaptive behaviour is explicitly implemented in the Protection Motivation Theory [19], PADM [20] and the Theory of Planned Behaviour [21].

Table 2 indicates that none of the main theories focusing on adaptive behaviour is considering social vulnerability as a driver or factor, whereas most of them do include individual risk perception. Overall, the terms of vulnerability or adaptation are rarely

Table 2
Theories with a focus on adaptation, implementing vulnerability or risk perception.

Theory	Focus on adaptation	Contains the term 'vulnerability'	Contains the term 'risk perception'
Driver-Pressure-State-Impact-Response (DPSIR)	DPSIR is describing a chain of causal links starting with 'driving forces' (human activities) through 'pressures' (risks, emissions) to 'states' and 'impacts' (on ecosystems, humans and functions), eventually leading to societal response (e.g., policy choice) and feedback from the environment.	no	no
Health Belief Model (HBM)	HBM links beliefs and expectation of consequences to behaviour. People's beliefs, perceived exposure, perceived benefits of action, barriers to action, and self-efficacy explain engagement. A stimulus, or cue to action, must also be present in order to trigger the change of behaviour.	no	yes
Protective Action Decision Model (PADM)	PADM informs how the processing of information from social and environmental cues shapes behaviour (see Table 1).	no	yes
Theory of Planned Behaviour (TPB)	TPB links beliefs to behaviour. The theory asserts that three core components, attitude, subjective norms, and perceived behavioural control, shape an individual's behavioural intentions. In turn, behavioural intention is considered the most proximal determinant of human social behaviour.	no	yes

addressed explicitly in the frameworks identified. However, some relations or applications of related terms and fields, such as social capital are mentioned, as well as inequalities. The findings show that even renowned and comprehensive frameworks about behaviour or motivation theories are coming short to explicitly express how the dimensions of vulnerability or adaptation could be theoretically structured.

Symmetrically, in the most commonly used frameworks of social vulnerability in DRR [22–27], risk perception is not addressed explicitly. While obstacles to adaptation are mentioned in the considered frameworks, risk perception is not implemented among the factors. Other frameworks exist in related fields such as communications or management. For example, the Transtheoretical Model of Change (TMM) [28] focuses on behaviour and barriers for change that linger in different phases of contemplation and action; it does not explicitly combine vulnerability, perception and/or adaptation either. Nevertheless, studies in disaster risk social vulnerability do acknowledge that different social groups have different forms of perception and knowledge [29]. They are often deemed key for better understanding community vulnerability and disaster risk reduction [66,83]. This includes for example the integration of indigenous and scientific knowledge [30], or the role of building trust through social collaboration [31].

The blind spot can thus be found in all three subfields, as none of the currently most in use theories, neither in risk perception, nor in adaptive behaviour, nor in social vulnerability, explicitly connects vulnerability with perception. The identification of this gap is consistent with recent findings from surveys among experts [17] and from recurring conferences [32]. In existing theories, the individualistic and psychological approaches are dominant to study risk perception. Still, their current self-reinforcing use loop might lead to overlook the need to consider social vulnerability as a possible factor.

2.2. Empirical studies

While empirical studies of risk perception have extensively covered individual aspects and usually implement socio-demographics variables, only few have explicitly studied the impact of social vulnerability (e.g., Refs. [6,33,34]). Some characteristics are more often gathered to explain disaster risk perception. For example, older people are often reported in empirical studies to perceive higher risk [35,36]. Older and wealthier people have been found to have higher perceptions and consequently adopt more prevention measures [74]. The longer one lives in the same place, the better one perceives the risk [37]. The more social and cultural capital people have, the more informed they are about risks [35,37]. White males have been found to be less informed than a woman or a person from a minority group [84]. The least educated are the most concerned about flood risk [85]. This effect is related to the relationship between education and income [38]. Ethnicity, social structure, and cultural grid have also been found to be explanatory variables [39,79]. Many more characteristics in qualitative studies or variables in quantitative studies can be found in connection with risk perception in social vulnerability or adaptation studies. Reviews of risk perception factors often mention all these facets and stress previous experience as a key factor [40,41]. Caution of caveats and generalisations are also provided – for example, that such findings on certain populations groups should not represent the stereotype [84].

CCA studies focusing on risk perception have a slightly different perspective. Extreme events are a conceptual bridge to traditional lines of social vulnerability studies regarding disaster risk perception. But CCA also captures perceptions of behavioural and societal change to more sustainable behaviour and everyday processes [64]. Heterogeneous groups again play a major role in such studies, for example, the sub-narratives leading to inaction due to conflicting interests, resource distributions and more [42,76]. This aligns with traditional findings in political security literature that identifies major conflicts within resource distribution, values, ideologies, coordination of action and epistemic knowledge [43].

Whilst many studies focus on a few isolated demographic indicators, e.g., age, gender, or education [38,40] or conflate vulnerability with hazard exposure [86], vulnerability is multidimensional and independent from exposure [27]. While many disciplines have different ways of defining, measuring, and assessing social vulnerability [44], and factors have been said to be limitless, dynamic, or context dependent [29,45,46], there is a growing convergence in quantitative studies on the main determinants of social vulnerability: demographic characteristics, socioeconomic status, discrimination and disability, and to a lesser extend living or housing conditions and tenure [47]. Intersectional approaches have highlighted that vulnerability is not the sum of discrete independent characteristics and cannot be boiled down to age, gender, education or even income [1]. As a result, recent publications have suggested to study the locally varying specific intersections of vulnerability drivers to advance the understanding of social vulnerability [48]. In contrast, very few studies have explored the relationships between social vulnerability, risk perception (e.g., Refs. [35,36]) and/or adaptive behaviour (e.g., Refs. [49,50]). Moreover, recent studies have suggested that vulnerable groups could be more uncertain about risks, have insufficient knowledge, and might be misrepresented in disaster risk perception studies [37,87].

3. Survey on floods in Paris – data and methods

To deepen the investigation of the impact of social vulnerability on risk perception, risk awareness and adaptive behaviour and help bridge this theoretical gap, we use a unique dataset of 5,000 respondents in Paris, France, following a series of floods. Paris is a 13 million inhabitant metropolitan area where more than one million people are directly exposed, and up to five million are indirectly exposed to floods [51]. The survey followed two flood events in 2016 and 2018, requiring large-scale evacuations, after one major European flood exercise in 2016 [77]. The survey was administered face-to-face in 2022 to a socially and spatially stratified random sample of 5,000 respondents. About half of the sample comprised of residents living in the official 100-year floodplain. One-third lived 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 stratified random sampling technique using both geographically based strata and social strata produced a sample representative at different spatial scales

(municipality, county, metropolitan region) and different exposure levels across the Paris metropolitan area. The participants were randomly recruited for each location within the Paris metropolitan area until the location-specific social quotas were fulfilled. This approach overcomes drop-out or response rate issues while quotas control for potential biases. The questions asked are detailed in the appendix.

We use this unique dataset and novel approach to confront the common assumption that previous hazard experience is the main driver of risk awareness and risk perception levels, and that risk communication campaigns are effective to raise awareness and align risk perceptions with the actual levels of exposure. We then explore social vulnerability as an alternative explanation, and finally we compare the explicative power of these different hypotheses. This results in a series of testable hypotheses:

Hypothesis 1. Previous hazard experience is the main driver of risk perception

H1a. Previous hazard experience leads to a more accurate perception of hazard exposure

H1b. Previous hazard experience increases confidence but also worry

H1c. Previous hazard experience increases flood perception levels

Hypothesis 2. Social vulnerability should be considered as an alternative explanation

H2a. Social vulnerability situations impact the perception of hazard exposure

H2b. Social vulnerability situations decrease confidence but increases worry

H2c. Social vulnerability situations impact flood perception levels

H2d. People in socially vulnerable situations are more likely to answer "I don't know"

Hypothesis 3. Information campaigns are effective to raise awareness and align perceptions

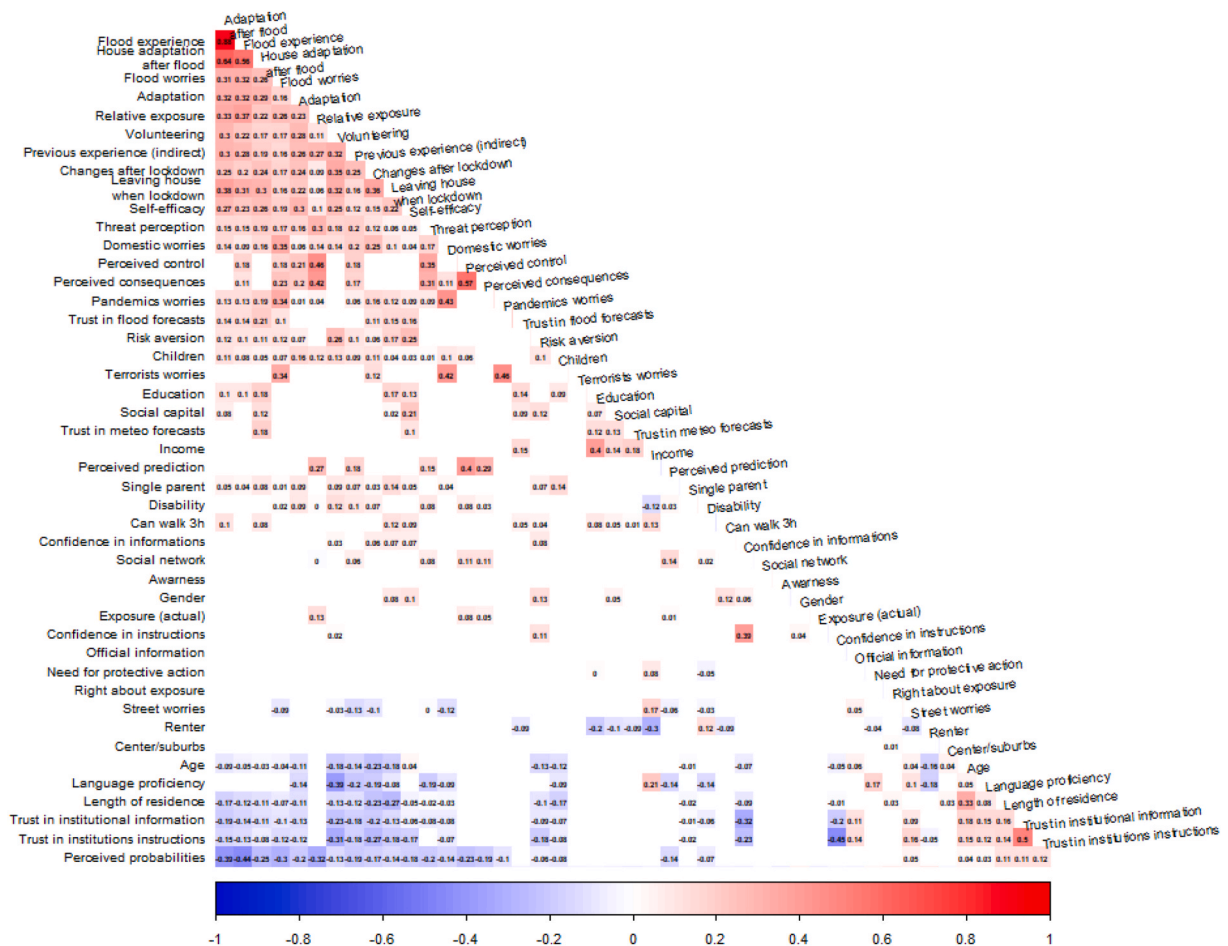


Fig. 1. Global correlation matrix (blank is not significant at 1 %).

- H3a.** Information campaigns lead to a more accurate perception of exposure
- H3b.** Information campaigns impact confidence and risk perception
- H3c.** Information campaigns impact flood perception levels
- H3d.** People who remember campaigns are less likely to answer "I don't know"

Hypothesis 4. Comparison of the power of the different explanations

H4. Compared to the most common assumptions, social vulnerability brings an additional level of explanation of disaster risk perception

For each hypothesis, we constructed a reference model for each independent variable (two for exposure, one for worry, two for trust and three for risk perception), including explanatory variables to represent the underlying concepts of a specific explanation, resulting in a variable number of explanatory variables from one hypothesis to another. The model compares the odds of each factor of an explanatory variable relative to a reference factor. This "all other things being equal" analysis, measuring the effect of each considered factor isolated from the effects of other explanatory variables included in the model. To avoid introducing an implicit selection bias [37], the respondents who express "don't know" are analysed in separate models.

We used logistic models to calculate the odds ratio for dichotomous independent variables. We used logistic regressions with proportional odds ratio models for the multinomial independent variables. These measure the effect of the explanatory categories on the probability of crossing an upper threshold of the independent variable while retaining the information resulting from the categories. We then used likelihood ratio tests to rank the information provided by each explanatory variable for each model. The test statistic is based on the difference in likelihood ratios between the full model, which includes all the variables, and the model under the null hypothesis with no specific explanatory variable. High likelihood ratio values mean that the null hypothesis cannot be rejected. In contrast, low values mean that the model retaining this specific variable improves the quality of the fit. We rejected the $p > 0.05$ and indicated the significance level of the test for each variable with overall p-values in order to assess whether this variable provides information about all the other variables in the model.

This is a higher-level explanatory analysis to investigate the amount of information captured by each variable in each model and the overall explanatory power of each hypothesis. The pseudo-R-squared (R^2) is a measure of the quality of the fit. We used the correction proposed by Nico Nagelkerke to ensure that the perfect fit value equals one. The Akaike Information Criterion (AIC) estimates the relative quality of models for a given set of data: the lower the value, the higher the model's ability to explain the dependent variable's variability.

4. Results of the survey

The global correlation matrix explores the relationships among all answers to the survey (Fig. 1). The Kendall's Tau correlation matrix reports inter-correlations among the demographic, social, psychological and behavioural variables. The results are presented as a heatmap, with statistically significant correlations ($p < 0.01$) highlighted in red for positive and blue for negative correlations. In the heatmap, the variables are reordered according to the angular order of the eigenvectors of the correlation matrix to help reveal the patterns in the data. The eigenvalues are related to the variances of the variables, the entire correlation matrix is needed to compute the resulting eigenvectors.

In Fig. 1, the flood exposure variables (perceived and measured), the adaptation scores (flood and pandemics), most flood perception variables (duration, frequency, consequences, prediction), higher worry for domestic accidents and pandemics, the oversight of children under the age of 12, and to a lesser extent, volunteering in civil protection, are positively and significantly related to each other (bottom right). Conversely, these variables are negatively correlated to age, length of residence in the same neighbourhood, ease of writing and speaking French, fear of walking at night in the street and trust in the government and institutions (bottom left). In this second cluster, the variables are positively and significantly related to each other: i.e., in the sample, older respondents are less likely to face linguistic isolation and more likely to trust the institutions. However, the memory of information campaigns and awareness of official flood information have less significant correlations and stand closer to the centre of Fig. 1 with most socio-demographic variables.

Table 3 suggests that previous hazard experience might have some significant links with perception of hazard exposure (H1a).

Table 3

Previous hazard experience and perception of hazard exposure.

	Right about direct exposure	Right about indirect exposure
Flood experience	*	***
Flood proofing (home)	–	***
Power cuts (indirect exposure)	**	***
Model	binomial	binomial
AIC	6924	6589
Pseudo R^2	0.004	0.049
N	5000	5000

Note: The following symbols represent the respective levels of statistical significance: _ n.s., * 5 %, ** 1 %, *** 0.1 %.

People with previous flood experience might seem to be more likely to be right about their direct flood exposure (home in the flood zone) and their indirect exposure (indicating that they could face power, water, heating, or phone outages, and sewer backflows, even if their home were not directly flooded). People with previous experience of severe power, water, and/or heating outages (indirect experience) might also have reported significantly different both direct and indirect flood exposure. Living in a flood-proofed (adapted) home was only reported as significantly related to being right about indirect exposure, not direct flood exposure, which is unexpected. However, the low model fit (pseudo $R^2 < 0.15$) of both models calls for greater caution regarding the robustness of these reported relationships (significant likelihood ratio test).

Table 4 suggests that previous hazard experience might have a significant impact on answers about flood worry, trust in flood forecasts, and trust in institutional flood information (H1b). While all variables – previous flood experience, having adapted after a flood, living in a flood-proofed home, and indirect (power cuts) experience – are all positively and significantly related to worry and trust, the low model fit of the three models calls for caution regarding the robustness of these relationships.

Table 5 reports that previous experience has a significant impact on flood perception levels (H1c). The better fit of the models suggest more robust relationships. All variables – previous flood experience, living in a flood-proofed home, and indirect (power cuts) experience – are all significantly related to answers about flood frequency, flood consequences, and relative perceived exposure (my home is more exposed to floods than other neighbourhoods).

Table 6 suggests that proxies of social vulnerability might have significant relationships with being right about their own direct and indirect hazard exposure (H2a). However, the low model fit of the two models calls for caution.

Table 7 shows that proxies of social vulnerability might have an impact on answers about flood worry, trust in flood forecasts, and trust in institutional flood information (H2b). However, the low model fit of the three models calls for caution regarding the robustness of at least some of these relationships.

Table 8 reports that social vulnerability has a significant impact on flood perception levels (H2c). While the models on flood consequences and on relative perceived exposure (my home is more exposed to floods than other neighbourhoods) have a low model fit, the model on flood frequency has a much higher explanatory power. In the case of flood frequency, almost all proxies of social vulnerability introduce significant differences in the answers when controlling for official flood exposure, with the exception of education attainment and being a single-parent family.

Table 9 reveals that some vulnerability proxies increase the likelihood of answering “I don’t know” to any of the previous questions on flood exposure, worry, trust, frequency, consequences or relative exposure (H2d). While the low fit of some models calls for caution, the model on worry about flood has a much higher explanatory power. In the case of flood worry, some vulnerability proxies have an impact on “I don’t know” answers, including gender, income, length of residence, language isolation, and being part of a minority.

Table 10 shows little support for a link between the memory of information flood risk campaigns or the awareness of official flood information and being right about their own direct and indirect hazard exposure (H3a). While awareness of official flood risk information has a no relationship with being right about their direct flood exposure, the low model fit of the two models calls for caution about the robustness of the other relationships.

Similarly, Table 11 reports that when controlling for official flood exposure, the evidence of an impact of information campaigns or flood information on flood worry or trust in flood forecast or institutional information is very weak (H3b). Contrary to expectations, the very low fit of the three models calls for caution about the robustness of the only few apparent relationships with worry or between information and trust.

In the same contrasting way to expectations, Table 12 reveals little support for a link between information campaigns or flood information and flood frequency, flood consequences, or relative exposure (my home is more exposed to floods than other neighbourhoods) (H3c). The very low fit of the three models challenges the robustness of the few apparent relationships.

Finally, Table 13 casts doubt on the hypothesis that people remembering flood information campaigns or aware of flood risk information would be less likely to answer “I don’t know” to any of the previous questions on flood exposure, worry, trust, frequency, consequences or relative exposure while controlling for official flood exposure (H3d). While a few significant correlations might seem to support an effect of campaigns and flood information on the answers, the very low fit of all the models challenges the robustness of any of these relationships.

Table 14 reveals that combining the constructs from all three sets of explanations allows to reach a higher explanatory power for all independent variables (H4). While some models have a low fit, four models reach a much higher explanatory power: worry about flood, flood frequency, flood consequences, and relative flood exposure. In the case of flood worry, previous experience, campaigns, flood information, as well as many proxies of social vulnerability, including age, gender, education, income, language isolation, and

Table 4
Previous hazard experience, worry and trust.

	Worry about flood	Trust flood forecast	Trust institutional flood information
Flood experience	***	***	***
Flood proofing (home)	*	***	**
Power cuts (indirect experience)	***	***	***
Model	multinomial	multinomial	binomial
AIC	13387	13876	6730
Pseudo R^2	0.09	0.028	0.039
N	5000	5000	5000

Note: The following symbols represent the respective levels of statistical significance: _ n.s., * 5 %, ** 1 %, *** 0.1 %.

Table 5

Previous hazard experience and flood perception levels.

	How often does flooding occur?	Floods have severe consequences	Relative perceived flood exposure
Flood experience	***	***	***
Flood proofing (home)	***	***	***
Power cuts (indirect experience)	***	***	***
Model	multinomial	multinomial	multinomial
AIC	14887	14642	13676
Pseudo R ²	0.258	0.118	0.154
N	5000	5000	5000

Note: The following symbols represent the respective levels of statistical significance: _ n.s., * 5 %, ** 1 %, *** 0.1 %.

Table 6

Social vulnerability and perception of hazard exposure.

	Right about direct exposure	Right about indirect exposure
Length of residence	—	—
Age	—	*
Gender	—	*
Education	***	***
Income	***	***
Language isolation	—	*
Single-parent	*	—
Children (under 12)	—	—
Disability	—	—
Minority	*	**
Tenant	*	—
Model	binomial	binomial
AIC	6892	6674
Pseudo R ²	0.032	0.049
N	5000	5000

Note: The following symbols represent the respective levels of statistical significance: _ n.s., * 5 %, ** 1 %, *** 0.1 %.

Table 7

Social vulnerability, worry and trust.

	Worry about flood	Trust flood forecast	Trust institutional flood information
Exposure	—	**	—
Length of residence	***	***	—
Age	***	—	***
Gender	***	***	**
Education	***	***	—
Income	***	***	*
Language	***	—	***
Single-parent	—	—	—
Children	—	**	—
Disability	—	—	—
Minority	***	***	***
Tenant	—	—	—
Model	multinomial	multinomial	binomial
AIC	13453	13769	6634
Pseudo R ²	0.125	0.093	0.076
N	5000	5000	5000

Note: The following symbols represent the respective levels of statistical significance: _ n.s., * 5 %, ** 1 %, *** 0.1 %.

being part of a minority, retain a significant impact on the answers. In the case of flood frequency and relative flood exposure, campaigns and flood information have no significant effect. Conversely, in the case of relative flood exposure, almost all social vulnerability proxies have a significant effect on the answers, with the exception of income and having children under 12 years of age. Overall, prior experience is the most robust explanation, followed by most proxies of social vulnerability, whereas the information, awareness and campaigns explanation are less often significantly associated with the answers.

Using this combination as a benchmark, we can observe how much each set of explanations deviates from the maximum expected explanation (higher pseudo-r², lower AIC). The models of [hypothesis 1](#) (H1) on prior hazard experience ([Tables 3–5](#)) and models of [hypothesis 2](#) (H2) on social vulnerability ([Tables 6–8](#)) are overall the models explaining the larger effects. Contrary to expectations, the models of [hypothesis 3](#) (H3) on information and communication campaigns ([Tables 10–12](#)) always have a low model fit, challenging the robustness of the few apparent relationships. As expected, the [H4](#) models combining all three explanations ([Table 14](#)) always reach

Table 8
Social vulnerability and flood perception levels.

	How often does flooding occur?	Floods have severe consequences	Relative perceived flood exposure
Exposure	***	*	***
Length of residence	***	***	***
Age	***	—	***
Gender	***	***	***
Education	—	—	***
Income	***	***	—
Language	***	—	***
Single-parent	—	—	*
Children	***	***	***
Disability	***	**	—
Minority	***	**	—
Tenant	***	—	—
Model	multinomial	multinomial	multinomial
AIC	15654	15010	14097
Pseudo R ²	0.223	0.088	0.114
N	5000	5000	5000

Note: The following symbols represent the respective levels of statistical significance: _ n.s., * 5 %, ** 1 %, *** 0.1 %.

a higher fit, meaning that combining the constructs from all three sets of explanations increases explanatory power.

5. Discussion

5.1. Discussion of results in relation to the hypotheses and literature

One of the main objectives of this article is to reconnect risk perception and social vulnerability. In line with hypothesis H2, we find that social vulnerability has a significant impact on a range of disaster risk perception answers. Our findings are overall consistent with the results of the very few previous empirical studies: social vulnerability [33,52,63,70], social exclusion [50], deprivation [53], living in a neighbourhood with greater levels of social marginality [6], or informal settlements [54], or self-reported vulnerability [36] do significantly increase the perception of levels of risk (H2c). However, contrary to previous findings, our results offer little support for an impact of social vulnerability on the awareness of exposure [34,73] (H2a) or the expressed levels of worry [55] and trust [35] (H2b). It is worth noting though that in our results, the intersection of social vulnerability proxies retaining significance is varying according to the dimension of disaster risk perception or awareness implemented. Nonetheless, we confirm in H2d that people in vulnerable situations are more likely to answer "I don't know" to many questions [37].

Reviews of risk perception studies often point to previous hazard experience as a key factor [40,41]. As expected, our results converge with previous studies on the impact of previous experience (H1a), as it has been shown to lead to a more accurate perception of exposure [38,56]. Direct physical and emotional experiences have also been found to correlate with worry [57], which matches our findings for H1b. Many studies have found that people with direct hazard experience subsequently express a higher perceived risk than people without experience (e.g., [58]), which is supported by our results for H1c. While fewer studies have examined the influence of risk communication [80,88], our results could not confirm previous suggestions that communication campaigns do lead to a more accurate perception of exposure [59] (H3a) and increase flood perception levels [14] (H3c). Contrary to expectations, the results could also not support an effect on trust in forecasts or institutional information (H3b). Similarly, the low explanatory power in our results challenges the idea that the awareness of official risk information and memory of information campaigns significantly reduces the likelihood of answering "I don't know" to any of the risk perception questions (H3d).

A novelty of our approach is to compare the relative explanatory power of these three sets of hypotheses (H4). When combining all explanations, previous hazard experience remains the most often significant, followed by most proxies of social vulnerability, whereas the information, awareness and campaigns lack robust explanatory power. This suggest that social vulnerability brings an additional level of explanation, and one more robust than risk information or communication campaigns.

5.2. Vulnerability and perception in the context of the main theories

We reveal the existence of a social vulnerability research gap, as not only theoretical frameworks of risk perception and adaptive behaviour overlook social vulnerability, but also symmetrically social vulnerability frameworks fail to explicitly address risk perception. Our empirical results highlight the need to refine existing theories to more systematically research the links between social vulnerability and risk perception. Theoretical frameworks are intended to guide the research of possible explanations. As a result of this social vulnerability gap, many studies might find it difficult to even consider vulnerability, implement it in their hypotheses, or test it among their explanations. In turn, this might explain the scarcity of the empirical evidence exploring the links between social vulnerability and risk perception published so far, and in a feedback loop offer little in support of explicitly connecting risk perception theories and social vulnerability frameworks. While some have recently suggested efforts in this direction [5,60], this is not straightforward: social vulnerability is a multidimensional and intersectional latent variable [1,47,48,61]. This reiterates early

Table 9

People in vulnerable situations are more likely to answer "I don't know".

	Don't know direct exposure	Don't know indirect exposure	Don't know flood worry	Don't know flood forecast	Don't know trust institution	Don't know flood frequency	Don't know consequences	Don't know relative exposure
Exposure	—	**	—	*	—	—	—	—
Length of residence	***	**	***	***	**	***	—	**
Age	***	—	—	—	—	—	*	—
Gender	—	***	*	—	—	**	—	***
Education	*	—	—	—	—	—	—	—
Income	***	***	**	***	—	***	—	***
Language	—	***	**	—	***	—	—	—
Single-parent	—	—	—	—	—	—	—	—
Children	—	—	—	—	—	**	*	—
Disability	—	*	—	—	—	—	**	—
Minority	**	***	***	***	—	**	—	—
Tenant	**	—	—	—	—	*	—	*
Model	binomial	binomial	binomial	binomial	binomial	binomial	binomial	binomial
AIC	3802	5770	1146	4345	1940	5774	2240	5021
Pseudo R ²	0.106	0.078	0.227	0.059	0.117	0.075	0.043	0.058
N	5000	5000	5000	5000	5000	5000	5000	5000

Note: The following symbols represent the respective levels of statistical significance: _ n.s., * 5 %, ** 1 %, *** 0.1 %.

Table 10

Information campaigns and perception of hazard exposure.

	Right about direct exposure	Right about indirect exposure
Do you remember any event or information campaign on flood risks?	**	***
Are you aware of any official information on the risks?	—	***
Model	binomial	binomial
AIC	6925	6716
Pseudo R ²	0.004	0.015
N	5000	5000

Note: The following symbols represent the respective levels of statistical significance: _ n.s., * 5 %, ** 1 %, *** 0.1 %.

Table 11

Information campaigns, worry and trust.

	Worry about flood	Trust flood forecast	Trust institutional flood information
Exposure	—	**	—
Campaigns	***	—	—
Official information	***	—	***
Model	multinomial	multinomial	binomial
AIC	13647	13962	6794
Pseudo R ²	0.038	0.008	0.022
N	5000	5000	5000

Note: The following symbols represent the respective levels of statistical significance: _ n.s., * 5 %, ** 1 %, *** 0.1 %.

Table 12

Information campaigns and flood perception levels.

	How often does flooding occur?	Floods have severe consequences	Relative perceived flood exposure
Exposure	***	—	***
Campaigns	***	***	***
Official information	***	—	***
Model	multinomial	multinomial	multinomial
AIC	16064	15112	14129
Pseudo R ²	0.053	0.028	0.070
N	5000	5000	5000

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

Table 13

Information campaigns and "I don't know" answers.

	Don't know direct exposure	Don't know indirect exposure	Don't know flood worry	Don't know flood forecast	Don't know trust institution	Don't know flood frequency	Don't know consequences	Don't know relative exposure
Exposure	*	**	—	**	—	—	—	—
Campaigns	***	***	**	—	***	***	***	***
Information	***	—	***	—	**	**	**	***
Model	binomial	binomial	binomial	binomial	binomial	binomial	binomial	binomial
AIC	3944	5861	1227	4418	1868	5850	2218	4911
Pseudo R ²	0.025	0.028	0.084	0.005	0.107	0.029	0.004	0.064
N	5000	5000	5000	5000	5000	5000	5000	5000

Note: The following symbols represent the respective levels of statistical significance: _ n.s., * 5 %, ** 1 %, *** 0.1 %.

critiques from the 1970s that underlying systemic risks and social drivers such as marginalisation must be better represented at the core of a theoretical risk frameworks [43]. Our empirical results prove that we can reach more robust explanations with more variance explained when including social vulnerability. Social vulnerability might be a better explanatory component than many common assumptions – such as risk communication – highlighting the necessity to refine existing theories to explicitly implementing the links between social vulnerability, risk perception, risk awareness, previous experience and adaptive behaviour. Possible avenues in that direction would be to try to connect the constructs from the Protective Action Decision Model with those of a social vulnerability model such as the Hazard-of-Place [89], or integrating social vulnerability or cohesion, place attachment, and community in existing models of preparedness [62].

Table 14

Combining the constructs from the three sets of explanations.

	Direct flood exposure	Indirect exposure	Worry about flood	Trust flood forecast	Trust institution	flood frequency	Flood consequences	Relative flood exposure
Exposure			—	***	—	***	—	***
Experience	*	***	***	**	***	***	***	***
Flood proof.	—	***	—	***	*	***	***	***
Indirect exper.	*	***	***	**	***	***	***	***
Length resid.	—	—	***	***	—	***	***	***
Age	—	—	**	—	***	—	—	**
Gender	—	*	***	***	*	**	***	***
Education	***	***	**	***	—	—	—	***
Income	***	**	***	***	—	***	***	—
Language	—	—	***	—	***	***	—	***
Single-parent	—	—	—	—	—	—	—	***
Children	—	—	—	***	—	—	—	—
Disability	—	—	—	—	—	—	—	**
Minority	—	*	***	***	***	—	***	***
Tenant	*	—	—	—	—	—	—	**
Campaigns	—	—	***	—	—	—	***	—
Official info.	—	***	**	—	***	—	*	—
Model	binomial	binomial	multinomial	multinomial	binomial	multinomial	multinomial	multinomial
AIC	6886	6493	13032	13681	6515	14513	14450	13268
Pseudo R ²	0.030	0.087	0.211	0.116	0.104	0.367	0.189	0.263
N	5000	5000	5000	5000	5000	5000	5000	5000

Note: The following symbols represent the respective levels of statistical significance: _ n.s., * 5 %, ** 1 %, *** 0.1 %.

5.3. Limitations

While we have based our selection of theoretical frameworks on a recent and large meta-analysis [8] and survey among experts [12], lesser-known theories, or published in other languages than English might exist. It is however important to highlight that the aforementioned studies do reveal a convergence on a small number of theories – not necessarily related to their demonstrated explanatory power – and a split by disciplinary perspectives or subareas of knowledge, each leading to theories focusing on different sets of explanations and/or producing frameworks that are not necessarily compatible. Moreover, whilst projects “frameworks” or “models” have been suggested, they are not yet in the same category as tested, validated, and recognized theoretical frameworks. For example, the BUILDERS project has introduced a model suggesting to link risk awareness with social capital on the basis of the intersectional perspective rather than the established theories [60]. This is further illustration that broader theoretical integration efforts are necessary to tackle the social vulnerability research gap in disaster risk perception.

In the empirical study, we had to limit the comparison of the explanatory power of social vulnerability with the two most common assumptions (risk information and communication campaigns) and explanations (previous hazard experience). Many more explanations would need to be explored, as suggested by the relatively low level of overall variance explained – even in our benchmark combining the three sets of explanations, meaning that other explanations might further improve the fit of the models to explain the answers. Besides, a more comprehensive implementation of social vulnerability would be to explicitly implement it as a latent variable, but this would require a different modeling approach, rendering the comparison with previous studies and between the statistical power of the different explanations much more challenging. This should be investigated in future research. In our survey, we had to limit the questions to concrete topics suited to the local experience of the people in Paris, France, and to the context of river floods. Given the current social vulnerability research gap, there is a broad need for further empirical studies, exploring other risk perception questions, case studies, disaster stages, and hazard types.

6. Conclusion

There is a shortage of explicit links between disaster risk perception and social vulnerability, as risk perception theories overlook social vulnerability as a possible explanatory factor, while social vulnerability frameworks neglect to explicitly address disaster risk perception. While both fields are well established, they seem shielded from each other by a self-reinforcing feedback loop: empirical studies might find it difficult to even consider vulnerability as relevant for perception from the current theories, and thus design the required research instruments, while the fragmented empirical evidence published thus far offers little incentive to explicitly connect risk perception theories and social vulnerability frameworks. We used a large representative sample from Paris, France (n = 5,000), after a series of floods to compare the explanatory power of social vulnerability with the two most common explanations of risk perception, previous hazard experience and risk information. We offer new insights by comparing the explanatory power of these three possible explanations, both taken individually and combined together. We find that the effects of vulnerability are stronger than those of risk information and communication campaigns. When taking social vulnerability into account, experience remains a robust

explanation, and combining the three sets of explanations increases explanatory power, suggesting that social vulnerability brings an additional level of explanation, more robust than common assumptions about risk information. We conclude that broader theoretical integration efforts are necessary to foster and consolidate the understanding of the relations between risk perception and social vulnerability. One implication of our study is that policies aimed at reducing social vulnerability might be more effective than risk communication campaigns in increasing awareness, preparedness and adaptive behaviour. Future research should systematically explore the impacts of social vulnerability on risk perception in a variety of case studies, disaster stages, and hazard types.

CRedit authorship contribution statement

Samuel Rufat: Writing – review & editing, Writing – original draft, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Alexander Fekete:** Writing – review & editing, Writing – original draft, Investigation. **Eric Enderlin:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Data curation.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ijdr.2025.105789>.

Data availability

Data will be made available on request.

References

- [1] C.H.A. Kuran, C. Morsut, B.I. Kruke, M. Krüger, L. Segnestam, K. Orru, S. Torpan, Vulnerability and vulnerable groups from an intersectionality perspective, *Int. J. Disaster Risk Reduct.* 50 (2020) 101826.
- [2] C. Kuhlicke, T. Masson, S. Kienzler, T. Sieg, A.H. Thieken, H. Kreibich, Multiple flood experiences and social resilience: findings from three surveys on households and companies exposed to the 2013 flood in Germany, *Weather, climate, and society* 12 (1) (2020) 63–88.
- [3] L. Köhler, T. Masson, C. Kuhlicke, Better prepared but less resilient: the paradoxical impact of frequent flood experience on adaptive behavior and household resilience, *Nat. Hazards Earth Syst. Sci.* 23 (8) (2023) 2787–2806. <https://nhess.copernicus.org/preprints/nhess-2023-64/nhess-2023-64.pdf>.
- [4] D.J. Geldenhuys, M.M. Levin, A. Van Niekerk, Risk management as a social defence against anxiety, *SA J. Ind. Psychol.* 38 (2) (2012) 1–9.
- [5] S. Rufat, A. Fekete, I. Armas, T. Hartmann, C. Kuhlicke, T. Prior, B. Wisner, Swimming alone? Why linking flood risk perception and behavior requires more than “it’s the individual, stupid”, *Water* 7 (5) (2020) e1462 <https://doi.org/10.1002/wat2.1462>.
- [6] S. Rufat, Towards a Social and Spatial Risk Perception Framework, *European Journal of Geography, Cybergeogeo*, 2015, <https://doi.org/10.4000/cybergeogeo.27010>.
- [7] K. Turesson, A. Pettersson, M.D.G. de Herve, J. Gustavsson, J. Haas, J. Koivisto, L. Nyberg, The human dimension of vulnerability: a scoping review of the Nordic literature on factors for social vulnerability to climate risks, *Int. J. Disaster Risk Reduct.* 100 (2024) 104190.
- [8] C. Kuhlicke, M.M. de Brito, B. Bartkowski, W. Botzen, C. Doğulu, S. Han, S. Rufat, Spinning in circles? A systematic review on the role of theory in social vulnerability, resilience and adaptation research, *Glob. Environ. Change* 80 (2023) 102672, <https://doi.org/10.1016/j.gloenvcha.2023.102672>.
- [9] S. Perlstein, Risk perception and interpersonal discussion on risk: a systematic literature review, *Risk Anal.* 44 (7) (2024) 1666–1680.
- [10] S.W. Chen, M. Keglovits, M. Devine, S. Stark, Sociodemographic differences in respondent preferences for survey formats: sampling bias and potential threats to external validity, *Archives of rehabilitation research and clinical translation* 4 (1) (2022) 100175.
- [11] V. Lorant, S. Demarest, P.J. Miermans, H. Van Oyen, Survey error in measuring socio-economic risk factors of health status: a comparison of a survey and a census, *Int. J. Epidemiol.* 36 (6) (2007) 1292–1299.
- [12] S. Rufat, M.M. de Brito, A. Fekete, E. Comby, P.J. Robinson, I. Armas, C. Kuhlicke, Surveying the surveyors to address risk perception and adaptive-behaviour cross-study comparability, *Nat. Hazards Earth Syst. Sci.* 22 (8) (2022) 2655–2672, <https://doi.org/10.5194/nhess-22-2655-2022>.
- [13] B.D. Williams, G.R. Webb, Social vulnerability and disaster: understanding the perspectives of practitioners, *Disasters* 45 (2) (2021) 278–295.
- [14] E. Lechowska, Approaches in research on flood risk perception and their importance in flood risk management: a review, *Nat. Hazards* 111 (3) (2022) 2343–2378.
- [15] A. Fekete, S. Rufat, I. Armas, A. Aslam, Survey results on preparedness, coordination, and lived experience of first responders in Germany and Romania 2021, *Die Erde* 154 (4) (2023) 145–158.
- [16] D. Osbergerhaus, H. Hinrichs, The effectiveness of a large-scale flood risk awareness campaign: evidence from two panel data sets, *Risk Anal.* 41 (6) (2021) 944–957.
- [17] A. Fekete, S. Rufat, Should everyone in need be treated equally? A European survey of expert judgment on social vulnerability to floods and pandemics to validate multi-hazard vulnerability factors, *Int. J. Disaster Risk Reduct.* 85 (2023) 103527.
- [18] J. Kerstholt, H. Duijnhoven, D. Paton, Flooding in the Netherlands: how people’s interpretation of personal, social and institutional resources influence flooding preparedness, *Int. J. Disaster Risk Reduct.* 24 (2017) 52–57.
- [19] D.L. Floyd, S. Prentice-Dunn, R.W. Rogers, A meta-analysis of research on protection motivation theory, *J. Appl. Soc. Psychol.* 30 (2) (2000) 407–429.
- [20] M.K. Lindell, R.W. Perry, The protective action decision model: theoretical modifications and additional evidence, *Risk Anal.: Int. J.* 32 (4) (2012) 616–632.
- [21] I. Ajzen, The theory of planned behaviour: reactions and reflections, *Psychol. Health* 26 (9) (2011) 1113–1127.

- [22] J. Birkmann, O.D. Cardona, M.L. Carreño, A.H. Barbat, M. Pelling, S. Schneiderbauer, T. Welle, Framing vulnerability, risk and societal responses: the MOVE framework, *Nat. Hazards* 67 (2013) 193–211.
- [23] O.D. Cardona, A.H. Barbat, *The Seismic Risk and its Prevention*, Calidad Siderurgica, Madrid, Spain, 2000.
- [24] S.L. Cutter, Vulnerability to environmental hazards, *Prog. Hum. Geogr.* 20 (4) (1996) 529–539.
- [25] DFID, Sustainable Livelihoods Guidance Sheets: Framework Introduction Vulnerability Transforming, DFID Editions, London, 1999.
- [26] B.L. Turner, R.E. Kasperson, P.A. Matson, J.J. McCarthy, R.W. Corell, L. Christensen, A. Schiller, A framework for vulnerability analysis in sustainability science, *Proceedings of the national academy of sciences* 100 (14) (2003) 8074–8079.
- [27] B. Wisner, P. Blaikie, T. Cannon, I. Davis, *At Risk – Natural Hazards, People's Vulnerability and Disasters*, Routledge, London, UK, 2004.
- [28] J.M. Prochaska, J.O. Prochaska, D.A. Levesque, A transtheoretical approach to changing organizations, *Adm. Pol. Ment. Health* 28 (2001) 247–261.
- [29] Z.T. Goodman, C.A. Stamatis, J. Stoler, C.T. Emrich, M.M. Llabre, Methodological challenges to confirmatory latent variable models of social vulnerability, *Nat. Hazards* 106 (2021) 2731–2749.
- [30] J. Mercer, I. Kelman, L. Taranis, S. Suchet-Pearson, Framework for integrating indigenous and scientific knowledge for disaster risk reduction, *Disasters* 34 (1) (2010) 214–239.
- [31] P.A. Arias, J.C. Villegas, J. Machado, A.M. Serna, L.M. Vidal, C. Vieira, Ó.A. Mejía, Reducing social vulnerability to environmental change: building trust through social collaboration on environmental monitoring, *Weather, climate, and society* 8 (1) (2016) 57–66.
- [32] S. Rufat, A. Fekete, Conclusions of the First European Conference on Risk Perception, Behaviour, Management and Response, CY University, Paris, France, 2019.
- [33] I. Armaş, Social vulnerability and seismic risk perception. Case study: the historic center of the Bucharest Municipality/Romania, *Nat. Hazards* 47 (2008) 397–410.
- [34] E. Beck, I. André-Poyaud, P.A. Davoine, S. Chardonnel, C. Lutoff, Risk perception and social vulnerability to earthquakes in Grenoble (French Alps), *J. Risk Res.* 15 (10) (2012) 1245–1260.
- [35] I. Armas, R. Ionescu, C.N. Posner, Flood risk perception along the Lower Danube river, Romania, *Nat. Hazards* 79 (2015) 1913–1931, <https://doi.org/10.1007/s11069-015-1939-8>.
- [36] I.O. Adelekan, A.P. Asiyani, Flood risk perception in flood-affected communities in Lagos, Nigeria, *Nat. Hazards* 80 (2016) 445–469, <https://doi.org/10.1007/s11069-015-1977-2>.
- [37] S. Rufat, W.W. Botzen, Drivers and dimensions of risk perceptions: revealing an implicit selection bias and lessons for communication policies, *Glob. Environ. Change* 73 (2022) 102465.
- [38] G. Wachinger, O. Renn, C. Begg, C. Kuhlicke, The risk perception paradox—implications for governance and communication of natural hazards, *Risk Anal.* 33 (6) (2013) 1049–1065.
- [39] P. Brown, A.J. Daigneault, E. Tjernström, W. Zou, Natural disasters, social protection, and risk perceptions, *World Dev.* 104 (2018) 310–325.
- [40] E. Lechowska, What determines flood risk perception? A review of factors of flood risk perception and relations between its basic elements, *Nat. Hazards* 94 (3) (2018) 1341–1366.
- [41] R.P. Bixler, S. Paul, J. Jones, M. Preisser, P. Passalacqua, Unpacking adaptive capacity to flooding in urban environments: social capital, social vulnerability, and risk perception, *Frontiers in Water* 3 (2021) 728730, <https://doi.org/10.3389/frwa.2021.728730>.
- [42] A. Rühlemann, J.C. Jordan, Risk perception and culture: implications for vulnerability and adaptation to climate change, *Disasters* 45 (2) (2021) 424–452.
- [43] A. Baird, P. O'Keefe, K.N. Westgate, B. Wisner, *Towards an Explanation and Reduction of Disaster Proneness*, University of Bradford, 1975.
- [44] B. Wisner, Vulnerability as concept, model, metric, and tool, in: *Oxford Research Encyclopedia of Natural Hazard Science*, 2016, <https://doi.org/10.1093/acrefore/9780199389407.013.25>.
- [45] J.C. Mah, J.L. Penwarden, H. Pott, O. Theou, M.K. Andrew, Social vulnerability indices: a scoping review, *BMC Public Health* 23 (1) (2023) 1253.
- [46] I. Armaş, A.C. Albulescu, D. Dobre, Towards managing vulnerability. A new model of systemic vulnerability, *Int. J. Disaster Risk Reduct.* 121 (2025) 105378.
- [47] O. Drakes, E. Tate, Social vulnerability in a multi-hazard context: a systematic review, *Environ. Res. Lett.* 17 (3) (2022) 033001.
- [48] E. Tate, S. Rufat, M.A. Rahman, S. Hoover, Beyond indices: profiles of social vulnerability for flood risk reduction, *Int. J. Disaster Risk Reduct.* (2025) 105250.
- [49] T. Grothmann, F. Reusswig, People at risk of flooding: why some residents take precautionary action while others do not, *Nat. Hazards* 38 (2006) 101–120.
- [50] A. Olofsson, S. Öhman, Vulnerability, values and heterogeneity: one step further to understand risk perception and behaviour, *J. Risk Res.* 18 (1) (2015) 2–20.
- [51] K. Fujiki, O. Finance, J. Hirtzel, C. Enaux, Flooding and inequality: a multilevel analysis of exposure to floods and poverty in French cities, *Appl. Geogr.* 164 (2024) 103193.
- [52] J. Dzialek, W. Biernacki, R. Konieczny, Ł. Fiedziński, P. Franczak, K. Grzeszna, K. Listwan-Franczak, Social vulnerability as a factor in flood preparedness. *Flood Memories, social Vulnerability and Risk Communication in Southern Poland*, 61–90, https://doi.org/10.1007/978-3-030-04594-4_4, 2019.
- [53] S. Sen, N.C. Nayak, W.K. Mohanty, C.K. Keshri, Vulnerability and risk perceptions of hydrometeorological disasters: a study of a coastal district of Odisha, India, *Geojournal* 88 (1) (2023) 711–731.
- [54] M.L.C. Da, H. Hangnon, M. Amalric, A. Nikiema, E. Robert, E. Bonnet, Revealing Social Vulnerability Profiles for Urban Flood Management: the Case of Ouagadougou (Burkina Faso), *European Journal of Geography, Cybergeo*, 2022, <https://doi.org/10.4000/cybergeo.38243>.
- [55] C.M. Thompson, R.J. Dezzani, Examining relationships between traditional vulnerability data proxies and hurricane risk perception indicators, *J. Risk Res.* 24 (8) (2021) 913–940, <https://doi.org/10.1080/13669877.2020.1773517>.
- [56] A. Scolobig, B. De Marchi, M. Borgia, The missing link between flood risk awareness and preparedness: findings from case studies in an Alpine Region, *Nat. Hazards* 63 (2012) 499–520.
- [57] N.C. Bronfman, P.C. Cisternas, P.B. Repetto, J.V. Castañeda, E. Guic, Understanding the relationship between direct experience and risk perception of natural hazards, *Risk Anal.* 40 (2020) 2057–2070.
- [58] W.J.W. Botzen, J.C.J.H. Aerts, J.C.J.M. van den Bergh, Dependence of flood risk perceptions on socio-economic and objective risk factors, *Water Resour. Res.* 45 (10) (2009) 1–15.
- [59] L.A. De Wolf, P.J. Robinson, W.W. Botzen, T. Haer, J.M. Mol, J. Czajkowski, Factors of influence on flood risk perceptions related to Hurricane Dorian: an assessment of heuristics, time dynamics, and accuracy of risk perceptions, *Nat. Hazards Earth Syst. Sci.* 24 (2024) 1303–1318.
- [60] C. Morsut, C. Kuran, B.I. Kruke, K. Orru, S. Hansson, Linking resilience, vulnerability, social capital and risk awareness for crisis and disaster research, *J. Contingencies Crisis Manag.* 30 (2) (2022) 137–147.
- [61] S. Rufat, E. Tate, C.G. Burton, A.S. Maroof, Social vulnerability to floods: review of case studies and implications for measurement, *Int. J. Disaster Risk Reduct.* 14 (2015) 470–486.
- [62] D. Paton, Disaster risk reduction: psychological perspectives on preparedness, *Aust. J. Psychol.* 71 (4) (2019) 327–341.
- [63] L. Antronico, F. De Pascale, R. Coscarelli, G. Gullà, Landslide risk perception, social vulnerability and community resilience: the case study of Maierato (Calabria, southern Italy), *Int. J. Disaster Risk Reduct.* 46 (2020) 101529.
- [64] G. Azócar, M. Billi, R. Calvo, N. Huneus, M. Lagos, R. Sapiains, A. Urquiza, Climate change perception, vulnerability, and readiness: inter-country variability and emerging patterns in Latin America, *Journal of Environmental Studies and Sciences* 11 (1) (2021) 23–36, <https://doi.org/10.1007/s13412-020-00639-0>.
- [66] S.L. Cutter, L. Barnes, M. Berry, C. Burton, E. Evans, E. Tate, J. Webb, A place-based model for understanding community resilience, *Glob. Environ. Change* 18 (2008) 598–606.
- [67] D. Edey, C.M. Thompson, J. Cherian, T. Hammond, Online local natural hazards education for young adults: assessing program efficacy and changes in risk perception for Texas natural hazards, *J. Geogr. High Educ.* 46 (3) (2022) 447–478.
- [70] S.L. Harlan, M.J. Sarango, E.A. Mack, T.A. Stephens, A survey-based assessment of perceived flood risk in urban areas of the United States, *Anthropocene* 28 (2019) 100217, <https://doi.org/10.1016/j.ancene.2019.100217>.
- [72] C. Kuhlicke, S. Seebauer, P. Hudson, C. Begg, P. Bubeck, C. Dittmer, S. Bamberg, The behavioral turn in flood risk management, its assumptions and potential implications, *Wiley Interdisciplinary Reviews: Water* 7 (3) (2020) e1418, <https://doi.org/10.1002/wat2.1418>.

- [73] M. Michetti, S. Ghinai, Climate-driven vulnerability and risk perception: implications for climate change adaptation in rural Mexico, *Journal of Environmental Studies and Sciences* 10 (3) (2020) 290–302.
- [74] D. Osberghaus, W. Botzen, M. Kesternich, E. Iurkova, The intention-behavior gap in climate change adaptation, ZEW Discussion Papers, No. 22-055, <https://www.econstor.eu/bitstream/10419/266645/1/1824563264.pdf>, 2022.
- [76] S. Rasool, I.A. Rana, S. Ahmad, Linking flood risk perceptions and psychological distancing to climate change: a case study of rural communities along Indus and Chenab rivers, Pakistan, *Int. J. Disaster Risk Reduct.* 70 (2022) 102787, <https://doi.org/10.1016/j.ijdr.2022.102787>.
- [77] S. Rufat, E. Comby, S. Lhomme, V. Santoni, Context matters when evacuating large cities: shifting the focus from individual characteristics to location and social vulnerability, *Environ. Sci. Pol.* 162 (2024) 103925.
- [78] S. Rufat, P.J. Robinson, W.J. Botzen, Insights into the complementarity of natural disaster insurance purchases and risk reduction behavior, *Risk Anal.* (2023), doi:10.1111/risa.14130. Rufat, S., Robinson, P. J., & Botzen, W. J. (2024). Insights into the complementarity of natural disaster insurance purchases and risk reduction behavior. *Risk analysis*, 44(1), 141–154.
- [79] F.S. Schoessow, Y. Li, J.R. Marlon, A. Leiserowitz, P.D. Howe, Sociodemographic factors associated with heatwave risk perception in the United States, *Weather, climate, and society* 14 (4) (2022) 1119–1131.
- [80] B. Walkling, B.T. Haworth, Flood risk perceptions and coping capacities among the retired population: a study of residents in a north Wales coastal town, UK, *Int. J. Disaster Risk Reduct.* 51 (2020) 101793, <https://doi.org/10.1016/j.ijdr.2020.101793>.
- [81] F. Roth, T. Prior, L. Maduz, A. Wolf. Social vulnerability in affluent contexts: an in-depth analysis of social vulnerability in Zürich, Center for Security Studies (CSS), ETH Zurich, 2018. <https://www.research-collection.ethz.ch/bitstream/handle/20.500.11850/321567/RR-Report-2018-SocialVulnerability.pdf>.
- [82] S. Rufat, C. Kuhlicke, Climate Captivity: When in-situ adaptation and moving out are no longer options, *Progress in Environmental Geography* (2025), 27539687251378494, <https://doi.org/10.1177/27539687251378494>.
- [83] P. Buckle, Re-defining community and vulnerability in the context of emergency management, *Australian Journal of Emergency Management* 13 (4) (1999) 21–26.
- [84] A. Olofsson, S. Rashid, The white (male) effect and risk perception: Can equality make a difference? *Risk Analysis* 31 (6) (2011) 1016–1032.
- [85] R.A. Bradford, J.J. O'Sullivan, Van der Craats, J. Krywkow, P. Rotko, J. Aaltonen, K. Schelfaut, Risk perception—issues for flood management in Europe, *Natural hazards and earth system sciences* 12 (7) (2012) 2299–2309.
- [86] A. Tanner, J. Arvai, Perceptions of risk and vulnerability following exposure to a major natural disaster: The Calgary flood of 2013, *Risk analysis* 38 (3) (2018) 548–561.
- [87] B. Noll, T. Filatova, A. Need, P. de Vries, Uncertainty in individual risk judgments associates with vulnerability and curtailed climate adaptation, *Journal of environmental management* 325 (2023) 116462.
- [88] W. Kellens, T. Terpstra, P. De Maeyer, Perception and communication of flood risks: A systematic review of empirical research, *Risk Analysis* 33 (1) (2013) 24–49.
- [89] S. Rufat, P. Hudson, E. Enderlin, Theoretical frameworks of risk perception and protective behaviour: an empirical comparison, *Natural Hazards* (2025) 1–71.