

The antecedents of risk perception in the context of natural hazards: A multi-level meta-analysis

Annalisa Theodorou ^{*,1} , Alessandro Milani ^{**,1} , Federica Dessi , Mei Xie ,
Marino Bonaiuto 

Department of Psychology of Developmental and Socialization Processes, Sapienza University of Rome, Italy

ARTICLE INFO

Keywords:

Risk perception
Natural hazard
Meta-analysis
Climate change

ABSTRACT

Risk perception is one of the major determinants of risk coping and, thus, of risk adaptation to natural hazards, whether resulting from climate change (e.g., sea level rise) or not (e.g., earthquakes). To understand how to increase an individual's risk perception of natural hazards, it is then crucial to identify the antecedents of risk perception. However, a cross-hazard meta-analysis of such a state of the art is still lacking. Thus, considering the determinants of risk perception for natural hazards, the aim was twofold: to identify the effect size of each determinant on risk perception and to find possible moderators of these relationships. Regarding the first aim, several antecedents taken from the literature proved to be significant, and they can be classified into three clusters: 1) factors related to the relationship individual-risk; 2) factors related to the relationship individual-community; and 3) individual factors (i.e., both sociodemographic and dispositional factors). The first cluster (i.e., individual-risk factors) showed the highest number of determinants with significant medium and large effects; then, the second cluster (i.e., individual-community factors) showed some determinants with significant small and medium effects; finally, the third cluster (i.e., individual factors) showed determinants having either only small significant effects (i.e., sociodemographic ones) or a few significant medium and large effects (i.e., dispositional ones). Regarding moderators, both social norms and the level of risk in the sample's area exerted significant effects, in some cases. Theoretical and methodological implications include theoretical advancements for natural hazards risk perception predictors modelling, and future studies' methodological choices.

1. Introduction

Natural hazards can be very destructive, and lead to devastation, both in terms of human lives loss and enormous economic damage. This is not specific of our contemporary era and human condition: “*It is far from easy to determine whether Nature has proved to man a kind parent or a merciless stepmother*” Pliny the Elder stated in his famous encyclopedia, the *Naturalis Historia* [1]. Currently, climate change highlighted, among other things, the importance of human adaptation to natural hazards [2]. According to the Hyogo Framework for Action adopted in 2005, a hazard is defined as “a potentially damaging physical event, phenomenon or human activity

* Corresponding author.

** Corresponding author.

E-mail addresses: annalisa.theodorou@uniroma2.it (A. Theodorou), a.milani@uniroma1.it (A. Milani).

¹ These authors share first authorship.

that may cause the loss of life or injury, property damage, social and economic disruption or environmental degradation” [3]. Here the expression “natural hazards” is referred to as hazards caused by natural processes [4].

According to a recent study [5], over the past century, the number of deaths imputable to natural hazards was subjected to a large decline due to earlier predictions, better preparedness for people and infrastructure, as well as a more coordinated response. In this scenario, involving people in preparedness and response to such events is becoming more and more crucial, also considering that many natural hazards are dramatically exacerbated by climate change [6]. Among the determinants of individuals’ action to protect themselves - both before, during, and after a natural hazard - one important aspect is the perceived risk associated with the event [7,8]. Among the three phases of resilience—preparedness, response, and recovery—preparedness is particularly critical for minimizing harm to people and property [9], making it the primary target for intervention. Considering the central role of risk perception in motivating preparedness behaviors toward natural hazards [10], and the importance of such measures in reducing damage and loss of life [11], it is necessary to focus on risk perception as the keystone of such a resilient adaptive process.

Risky circumstances demand appropriate evaluations to lead to successful protective actions. However, risk assessment by the population is hardly based on objective risk [7,12]. In fact, what has been found is that the risk as perceived by people is not a mere probability calculus, and it thus differs from what policymakers may consider [13]. This bias occurs because people are different: Thus, individual differences, and social and cultural differences too, may determine a variation in how they experience risk [14–20]. Since individuals infer risks most commonly without referring to statistics, it may also be biased in the way they calculate risks due to heuristics [19,21]. These aspects urge experts and policymakers to identify possible determinants and sources of bias when referring to individual risk perception. This contribution aims 1) to meta-analytically estimate effect sizes of different potential antecedents of risk perception for various natural hazards, and 2) to investigate the effect of possible moderators of such relationships. It consequentially aims to derive the relevant theoretical and methodological implications from the results too.

1.1. Risk perception

Risk perception is strongly related to the concept of uncertainty, conveying a sense that something of human value (including human life) is at stake, and the outcome is uncertain [22]. It can be defined as “the subjective assessment of the probability of a specified type of accident happening and how concerned we are with the consequences” ([13], p. 8). Although this definition is widely supported in the literature, Kaspersen and colleagues [23] - introducing the Social Amplification Risk Framework (SARF) - suggest that individuals have a broader and more comprehensive conceptualization of risk. Notably, the subjectivity of such assessments, which leads to numerous biases in risk estimation [21], makes it necessary to investigate what influences such changing perceptions. It is however difficult to refer to a general theory of risk perception, considering that it is a multidimensional construct based on individual, social, and cultural aspects [24].

Two classic theories studied what influences risk perception and, subsequently, leads people to protect themselves: these are the Health Belief Model (Rosenstock, 1974) and the Protection Motivation Theory [25]. On the one hand, Rosenstock's Health Belief Model refers to two types of beliefs, namely, perceived susceptibility (vulnerability) and perceived seriousness (severity), as individual perceptions leading to preventive (adaptive) behaviors. On the other hand, the Protection Motivation Theory identifies appraised severity, expectancy of exposure, and belief in the efficacy of coping responses as the cognitive mediating processes (the fear appeal) that determine protection motivation to engage to a protective response.

Similarly, subsequent classic conceptualizations refer to two dimensions, namely the “perceived likelihood of an event” and the “perceived severity of consequences” [13]. Nevertheless, scholars have raised questions on the possible role of emotions in risk perception and came out with a distinction between cognitive aspects of perceived risk (i.e., “perceived likelihood” and “expected consequences”) and more affective aspects related to emotions exacerbated by the potential event [26,27]. Regarding the affective component - drawing from appraisal theory - while it is often considered part of the risk perception process, it is predominantly conceptualized as a key antecedent of risk perception. This component acts as a mediator, channeling various social-psychological antecedents (such as uncertainty) into risk perception (see [28,29]). An additional factor named “susceptibility” (also referred to as “vulnerability” by some scholars) indicates “the likelihood of suffering some consequence given exposure” as opposed to “the likelihood of being exposed to the hazard” ([30], p. 136). Overall, risk perception has been studied by a variety of disciplines and, to date, there is no univocally accepted definition or standardized measure to better define the construct (see [30–33]).

Interestingly, it has been highlighted that there is one aspect, among the specific domains of risk perception, which provides useful insights into the demand for risk reduction from the population: namely, the “perceived consequences of a hazard” ([34,35]; [13]). Advocates of this perspective use the following explanatory example: Getting a cold is more probable, but consequences are less important than getting AIDS; thus, risky intercourses are perceived as deserving more risk management than shaking hands [34,35]. Moreover, it has been argued that probability is a concept closer to experts' risk forecast than lay citizens, and thus, more difficult to process by these latter [34]. In line with this reasoning, it seems that the severity of consequences, more than the probability of harm, affects the individual's motivation to protect oneself during the COVID-19 pandemic [36].

By comparing thirty risky events, Slovic and colleagues [37] pointed out that for lay people, and even more for experts, the perception of risk is comparable to the perception of the harmful consequences of the risk itself. Similarly, Böhm and Pfister [38] argued that the consequences attributed to risk are crucial in risk assessment, emphasizing the centrality given to the risk consequences in defining risk: “One aspect is the evaluation of potential consequences [...] This aspect corresponds to what is usually referred to as risk perception” ([38]; p. 462). Lindell and Perry [39] also reported that risk assessment can be related to the impacts that a natural event might cause. Empirically, Walpole and Wilson [30] demonstrated that this aspect of risk perception significantly explains the variance of the general measure more than other components (namely, affect, exposure probability, and susceptibility). All in all,

scholars generally agree that the likelihood of experiencing negative consequences is at the core of risk perception ([40]; [41]; [10]).

1.2. Research on the antecedents of risk perception across different natural hazards

Previous attempts to synthesize the literature on the role of the antecedents of risk perception regarding different natural hazards are limited. Available reviews on the topic often referred to broad reviews focused on various hazards (e.g., hazards in general, non-technological hazards; [19,42]) while other reviews addressed only a specific type of natural hazard, such as floods [31,43], mountain hazards [32], and earthquakes [44], neglecting others. The only review available on the antecedents of risk perception specifically addressing different types of natural hazards focused only on European research; thus, findings may be somewhat limited in their generalizability [10]. Moreover, almost all the above mentioned reviews neglect most of the psychological constructs traditionally investigated in relation to risk perception (e.g., personal dispositions, place attachment and identity, norms and values, self-efficacy).

From a more environmental psychology perspective, Bonaiuto and Ariccio [45] made a conceptual effort to systematize the antecedents of protective and coping behavior in the face of natural hazards, of which risk perception may be considered a direct predictor. They focused on resilient behavior before (preparedness), during (response), and after (recovery) the natural hazard event. In particular, these authors conceived three clusters of antecedents: 1) factors concerning the relationship between the individual and the risk, namely how the individual relates with the risk in their area of living (e.g., objective and subjective knowledge, and prior experience of the hazard); 2) factors concerning the relationship between the individual and the community, namely how the individual relate to the place and the community in which they live (e.g., sense of community, place attachment, social norms, social identity, and trust in authorities); and 3) individual factors, which are less likely to be modified, namely, a) sociodemographic (e.g., educational qualification, home ownership, residential tenure, having or not children, household size) and b) dispositional factors (e.g., self-efficacy and fatalism).

Regarding the first cluster, namely factors concerning the relationship between the individual and the risk, one of the most important antecedent identified in the literature of natural hazards such as floods, earthquakes, and mountain hazards is prior experience [10,19,31,32,44]. In particular, Wachinger et al. [10] showed that on one hand some studies reported positive effects on risk perception, highlighting how having experienced the event enhanced the perceived probability of its occurrence, thus increasing risk perception. On the other hand, others found negative effects, suggesting that having experienced the natural event, and having coped with it, gave the illusion that future similar events could be simpler to overcome. Thus, the authors hypothesized that the severity of prior experience, namely the extent of the perceived negative impacts of the event, rather than experience itself, is what heightens risk perception [10]. The literature found as another important antecedent of risk perception knowledge regarding the natural hazard and objective risk, specifically in the context of climate change perception [19,46,47], floods [43], and earthquakes [44]. Another important antecedent found in research on floods is worry [43]. Lastly, minor factors are preparedness [31,43,44], perceived likelihood and perceived magnitude of the event [10].

Regarding the second cluster, namely factors concerning the relationship between the individual and the community, one of the most important antecedents identified in the literature is trust in authorities ([10,31,32,43]; see also [19]). Wachinger et al. [10] report highlighted how some studies showed a negative effect, presumably because people with high trust are relieved from the burden of responsibility of taking action to protect themselves and see future natural events as less probable and less severe. At the same time, however, a certain level of trust is expected, in order to follow advice from authorities under risky situations, leaving the question open with respect to the role of this variable in risk perception. Other minor factors found in this cluster are media coverage and trust in the source of information [10].

Table 1

Summary of the antecedents and open questions identified in available literature reviews.

Antecedents	Importance suggested by the literature			
	Primary	Secondary	No influence	Open questions
Factors concerning the relationship between the individual and the risk	– prior experience [10, 19,31,32,44] – knowledge and objective risk [19,43, 44] – worry [43]	– preparedness [31,43,44] – perceived likelihood and perceived magnitude of the event [10]		– direction of the effects of prior experience [10,44]
Factors concerning the relationship between the individual and the community	– trust in authorities ([10,31,32,43]; see also [19])	– media coverage [10] – trust in the source of information [10]		– the direction of the effects of trust in authorities [10]
Individual factors	Sociodemographic factors – gender [43]	– gender [19] – age and education [43]	– gender, age, education, and income [19] – income [43]	– strength of the effects of sociodemographic variables [10, 19,32]
	Dispositional factors – worldviews and values orientation [10, 19] – optimistic bias [19, 44]	– personality traits [19]		

Regarding the third cluster, namely individual factors, and in particular sociodemographic factors such as gender, age, income, and education, they resulted only modestly associated with risk perception ([19]; see also [48]). Only in the review by Lechowska [43] on floods, gender emerges as a primary influencing factor among other sociodemographic antecedents resulted only weekly, or not at all associated with risk perception. Results are inconsistent with respect to variables such as gender, age, education, and income in the context of mountain hazards, earthquakes, and natural hazards in general [10,32,44]. Regarding dispositional factors, biospheric and altruistic values have been found as antecedents of climate change risk perception, while personality traits seem to be only weakly associated or to not be associated at all with risk perception of natural hazards [19,49]. Other dispositional factors identified are optimistic bias [19,44], and worldviews [10].

A summary of the antecedents and open questions identified in available literature reviews are reported in Table 1. All in all, the studies that examined the antecedents of risk perception in natural hazards are limited; and, so far, they produced inconsistent findings [10,19,32,44]. Accordingly, from a theoretical perspective, we observe a paucity of theories interested in what contributes to shaping risk perceptions in relation to natural hazards through the systematic identification of specific antecedents of risk perception. In fact, the only attempts found are some theorizations proposing a general rationale for how risk perceptions are created, such as the Cultural Theory of Risk [50], the Social Amplification of Risk Framework [23], and later conceptualization of the Protection Motivation Theory (see [51]), in which some theorizations has been proposed but remained mostly unexplained [52]. This is consistent with 1) the heterogeneous picture of this field of research made by previous scholars, with little agreement on basic theoretical issues [32,42]; 2) theoretical gaps identified across research regarding different hazards, such as floods, mountain hazards, and earthquakes (see [31,32,43,44]); as well as 3) the inconsistent findings regarding various antecedents investigated so far (e.g., prior experience, trust in authorities, sociodemographic variables).

1.3. The need for a meta-analysis on natural hazards' risk perception determinants

Building on classic theories of risk and behavior [23,25,39,50,51,53] and various literature syntheses on the topic (e.g., [8,10,19,32]) listed above, it can be hypothesized that a heterogeneous range of specific variables - such as worldviews, self-efficacy, coping appraisal, prior experience, communication, social norms, as well as moral and value-based considerations, and emotional responses - play a primary role in influencing risk perception. However, no previous attempts in quantitatively synthesizing the available literature - specifically focused on risk perception of a variety of natural hazards with a broad focus on both international and grey literature - were found. As testified by previous attempts at synthesizing the literature on the subject, it is necessary to investigate common factors that drive the risk perception of various natural hazards [10,19,42,45] and concurrently capture differences between specific natural hazards (e.g., [8,54]). Moreover, we extend the study of risk perception to risk related to climate change. This is based on the similarities found in the literature concerning natural hazard risk and climate change risk in the investigation of similar antecedents [19]. In fact, the manifestation of climate change appears mainly through either slow-onset or fast-onset natural events, e.g., heatwaves, droughts, floods, sea-level rise [55].

Lastly, despite risk perception of natural hazards being an important factor in risk management, as studied by a variety of disciplines [56], important questions are yet to be answered, such as: the direction of the effects of previous experience and trust in authorities as highlighted by Wachinger et al. [10]; the strength of the effects of sociodemographic variables [10,19,32]; and the effects of variables for which inconsistent findings were found across reviews and/or for which a quantitative synthesis is not available, e.g., values, social norms, self-efficacy, personality traits, and place attachment [45].

To draw conclusions and fill the gap regarding the direction and strength of the effects of antecedent variables across the available studies, and to find specific conditions that can alter these effects (i.e., moderators), a meta-analysis approach is needed. According to the psychometric paradigm, which aims at studying perceived risk perception through questionnaires and quantitative analysis [57,58], the main focus of this contribution is to present methods and results of different meta-analyses on the antecedents of risk perception in the context of natural hazards. Findings will then be discussed considering the available literature and theory, and they will be used as a significant starting point for delineating a wider theoretical model, for suggesting improvements in future research, and for offering practical implications through a data-driven approach. According to Grounded Theory (Glaser & Strauss, 1967), in reviews and meta-analyses, such an approach supports the iterative generation of categories and hypotheses as new empirical studies are incorporated, allowing researchers to predict patterns of similarity or divergence across findings. By prioritizing theory development grounded in data rather than formulating predefined assumptions, this approach may be especially valuable in addressing inconsistencies observed in the literature of risk perception.

More specifically, the aim of this work is twofold: 1) to estimate effect sizes of different potential antecedents of risk perception in the domain of natural hazards, providing a quantitative summary of the available research [59]; 2) to investigate the effect of possible moderators of such relationships. In particular, the conceptualization made by Bonaiuto and Aricchio [45] is taken as a starting point, as it takes a specific focus on environmental psychology variables, especially regarding variables related to the ecological and social context, and individual differences. Regarding the first aim, following Bonaiuto and Aricchio's [45] framework and based on the findings of the available research syntheses reviewed above, we expect to establish the direction of the effects of previous experience and trust in authorities, to find the strength of the effects of sociodemographic variables, as well as to identify the most important predictors of risk perception.

Regarding the second aim, following van Valkengoed and Steg [8], we examine the role of the measurement of previous experience, i.e., absence/presence of experience of the event and the frequency of the experience (e.g., number of experienced events), the possible difference between subjective and objective knowledge, and injunctive and descriptive norms, expecting no differences. Since differential effects regarding the type of natural hazard considered, as well as gender, age, and education were not contemplated by

previous literature, we investigate the role of these moderators too. Lastly, we collect data on methodological differences between studies that may potentially affect the results too: namely, the employment of a case study, rural or urban sample, the level of risk in the area where the sample was engaged, type of risk measured (health, economic), and risk attribution measured (to self/others). Grey literature is included, and the potential differences in results with published research are assessed.

2. Method

The methodology adopted for the meta-analyses followed the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) statement [59,60]. On thirty-five possible antecedents detected, after preliminary analyses, thirty-two meta-analyses are conducted in total (for more information on the selection of variables for the meta-analyses, see below the paragraph “3.1 Preliminary Analysis: Normality of Distribution”).

2.1. Literature search

The literature search is aimed at identifying the studies that focused on the antecedents of risk perception in the domain of natural hazards. To build the query string, the focus is on defining the research topic (e.g., natural hazards), defining the dependent variable (i.e., risk perception), and providing keywords for a set of independent variables identified in the literature. Regarding this latter point, such an approach serves to broaden and better direct the search; however, it is also possible to consider additional independent variables from the resulting records that are not originally included in the query string. In this way, an attempt is made to include as much as independent variables as possible.

In order to define which natural hazards have to be considered, by following the United Nations definitions [6,61] the search includes: 1) geological or geophysical hazards, originating from internal earth processes (e.g., earthquakes, volcanic activity, landslides; [6]); 2) hydro meteorological hazards, of atmospheric, hydrological, or oceanographic origin (e.g., cyclones, floods; [6]); 3) natural hazards considered as effects of climate change (e.g., sea level rise, loss of biodiversity; [61]).

In order to better define the dependent variable and all possible independent variables by using pertinent keywords, one available review on the antecedents of risk perception of various natural hazards [10], another review on the determinants of risk perception limited to floods [43], and a more recent review which comprises risk perception in different domains, also outside natural hazards [19], are consulted. A more general search on the strings used in the literature on similar topics is also conducted (e.g., [8]). The query

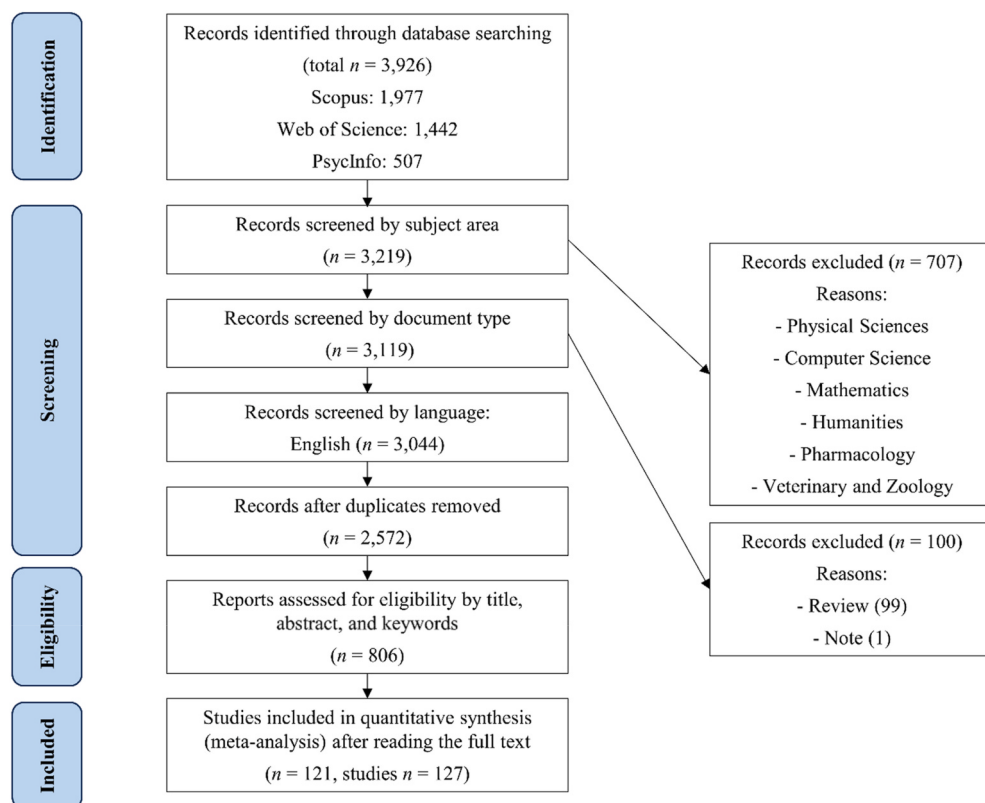


Fig. 1. Flow diagram, drawn up according to the PRISMA statement, graphically presenting details of the literature search and the number of records screened, assessed, and included.

string (Table S1) is then composed of keywords organized into three interdependent levels: 1) keywords that define the research topic (i.e., natural hazards); 2) Keywords that define the dependent variable (i.e., perceived risk); 3) keywords that define a set of independent variables retrieved from the available literature (e.g., knowledge, trust in authorities, age).

The bibliographic search was carried out through three of the most important databases for the psychological literature, namely, Scopus, Web of Science, and PsycINFO, on June 13th, 2023. The search results in a total of 3926 records (in detail: Scopus: 1977; Web of Science: 1442; PsycInfo: 507).

2.2. Inclusion and exclusion criteria

The initial pool of records identified by the query string is screened through automatic search tools, provided by the databases Scopus and Web of Science, by: 1) subject area, mostly excluding disciplines that do not involve studies on human participants (e.g., physical sciences, veterinary) and risk perception of natural hazards (i.e., pharmacology); 2) document type, excluding records which do not present data (i.e., reviews and notes); 3) language, excluding records not written in English. After this preliminary screening, duplicates are also excluded using the platform EndNote [62]. At this point, three researchers (AT, AM, MX) independently reviewed a total of 2572 records by title, abstract, and keywords, resulting in 806 selected records. Then, three researchers (AT, AM, FD), after having filtered further and independently the records by full text, arrived at the final number of 121 records selected (127 studies). Search queries are presented in Table S1. In Fig. 1, a flow diagram describing the selection process of the articles is presented.

Inclusion criteria consider full texts located online and accessible in scientific databases. Non-accessible full texts are personally asked to the corresponding author(s). In particular, 9 full texts are received out of 27 requested (response rate: 33.33%). Included studies have also to present quantitative analysis and, specifically, to investigate the association between a certain antecedent of risk perception (i.e., a specific predictor) and the risk perception measurement (i.e., the dependent variable). Moreover, to be included, they have to report specific statistical coefficients (i.e., effect sizes) to express the association between an independent variable and the dependent variable (e.g., Pearson's r , standardized correlation coefficients, Odds Ratio). When the considered effect sizes are correlations, if theoretical reasons apply, variables are considered as antecedents of risk perception, also in cases in which the original study does not view them as such.

Corresponding authors are contacted to request specific statistics when studies present appropriate data without providing the necessary coefficients. In particular, since standardized coefficients from regression models with multiple predictors differ from correlations, especially when there are high correlations among them, caution should be taken when including such regression coefficients in meta-analyses [63]. For this reason, in such cases, authors are directly contacted to request Pearson's r coefficients to avoid using coefficients from multiple regression analysis as much as possible. In total, in 172 cases, authors were personally contacted, and 25 provided the requested statistics (response rate: 14.53%), therefore only these are included if other statistics were not available (e.g., standardized regression coefficients). For longitudinal studies, associations between variables measured at baseline (first data collection before the intervention) are considered. For experimental studies, only those presenting associations between variables measured in the control group are included.

2.2.1. Inclusion and exclusion strategy regarding the definitions of risk perception

The intent of this work is to give back a general overview of the antecedents of risk perception investigated in the literature. According to that principle, in the definition of risk perception, the query string is built to be as general as possible to include the largest number of studies. In filtering the records to be included, though, researchers have been forced to make a reflection on the studies to be included based on the risk perception measurement. The initial pool of records comprised studies that used very different, and mostly mixed, measures of risk perception (e.g., several unidimensional scores that comprised different combinations of the construct's aspects). This is in line with what has been found by previous research (e.g., [30–33,43]). Moreover, the remaining studies used very different conceptualizations of risk perception, often measuring one or two aspects of risk perception (e.g., likelihood and severity, negative emotions alone). Retaining all these studies would have led to a high risk of comparing different constructs. This urged us to identify a simpler measure that would, however, capture the core of risk perception definition and efficiently synthesize the literature on the subject.

Thus, during the full-text selection phase, a procedure that retained studies measuring risk perception using a general holistic measure is employed. This involves directly inquiring about the perceived risk associated with the specific hazard (e.g., *How risky is X?*; [33]). This decision is in line with the results by Wilson and colleagues [33], who investigated how risk perception is operationalized in the literature, and found that the general measure of risk perception is used in the highest percentage of studies, i.e., 40%.

Since selecting only these studies would have meant excluding more than half of the records, measures focused on the expected consequences of the natural hazard have been included too. The expected consequences are considered for three reasons. First, this aspect of perceived risk is found to significantly explain the variance of the general measure (.29, $p < 0.001$) more than the other three dimensions of risk perception, namely affect (.09, ns.), exposure probability (.10, $p < 0.05$), and susceptibility (.10, ns) in the context of natural hazards [30]. This is in line with what has been found in prominent theories of risk perception, namely that the perceived consequences of the hazard are at the core of risk perception and are considered the component that drives risk perceptions more than the other components ([38,39]; [34,35]; [37]). Second, in the selected studies, this is the most recurrent measure, common to most studies, allowing us to include the maximal quantity of studies and to run the largest number of meta-analyses. Third, it has been argued that it is precisely this aspect of risk perception that motivates the most in adopting protection measures by lay citizens, and thus, the one that provides useful insights for risk reduction [13].

Few studies considered risk components (e.g., perceived likelihood) as predictors of holistic and/or consequence-related risk

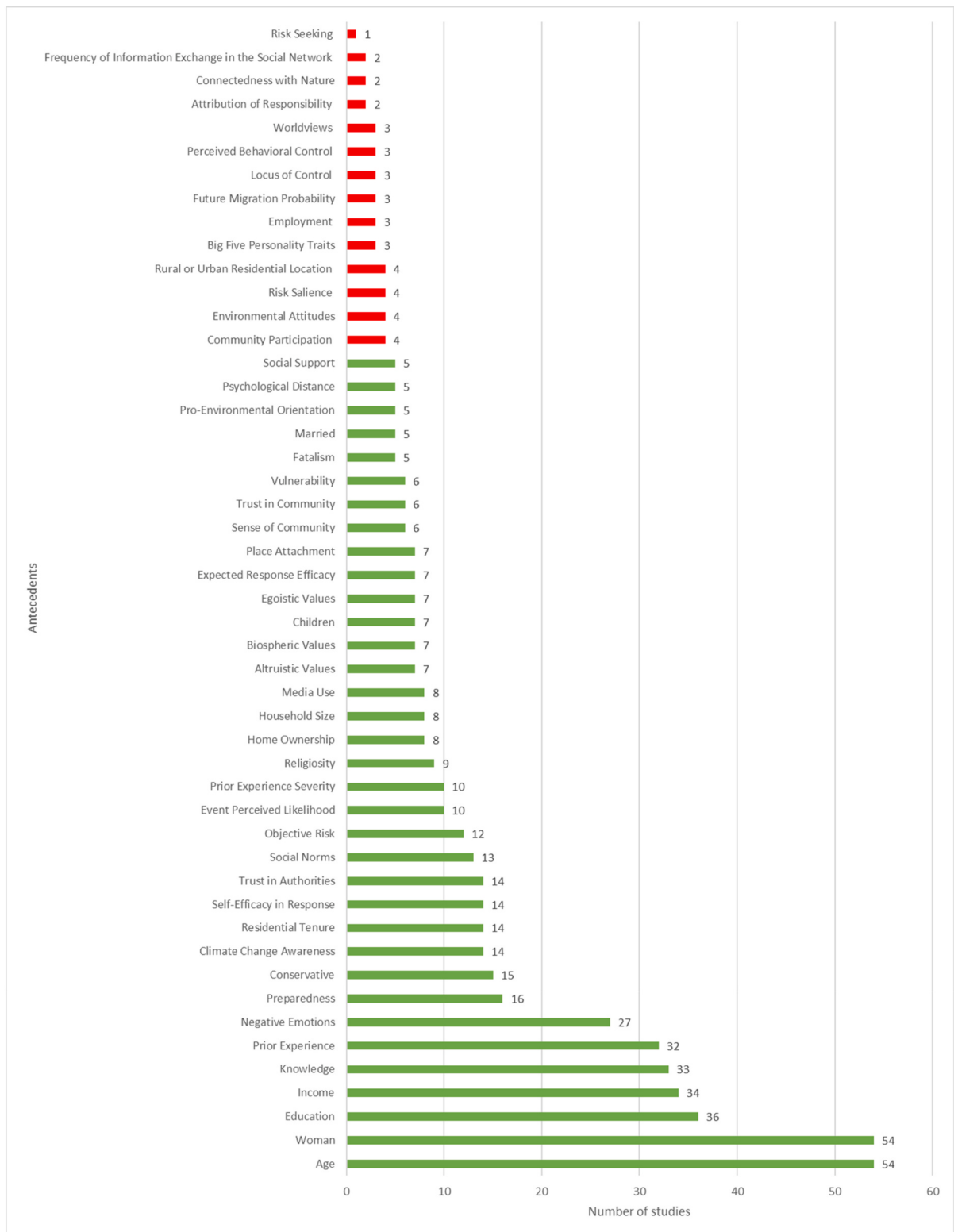


Fig. 2. Number of studies by each antecedent considered

Note. Excluded variables = red bar; included variables = green bar.

measures [30,64]. Given that our analyses were based on Pearson's correlations (no causality), these variables were included and treated as independent variables to investigate their relationship with the outcome variable.

2.3. Data analysis strategy

Effect sizes are grouped, and meta-analyses are conducted if a minimum of five studies is achieved [65]. To establish if a certain study would qualify to describe the relationship between a certain independent variable and risk perception, items and response scales of the independent variable are also examined. If the items do not match the specific independent variable of interest (e.g., items asking about self-efficacy associated with a variable labeled "social vulnerability"), the study is excluded from that specific meta-analysis (e.g., vulnerability and risk perception) and, possibly, collocated in a different one (e.g., self-efficacy and risk perception).

In some cases, multiple effect sizes are collected for each sample between a specific antecedent and the dependent variable risk perception. This happens when, for instance, multiple risk perceptions are measured in the same study (e.g., the relationship between the same antecedent, self-efficacy, and personal and global risk perceptions). Including both correlations separately would have violated the standard meta-analytical assumption of independent data. Since the recent literature on meta-analysis suggests that dependent effect sizes can be managed with multi-level modeling (e.g., [66]), multi-level meta-analyses were conducted. Whenever effect sizes are coming from studies that used reverse-coded items (e.g., response inefficacy) as compared to other studies (e.g., response efficacy), the effect is reversed (i.e., from negative to positive or vice versa) in order to include the study together with the other ones.

All the collected effect sizes are transformed into Pearson's r before conducting each meta-analysis. Spearman's rho (ρ_s) is converted using the formula by Rupinski and Dunlap [67]. Standardized coefficients (β) are transformed in Pearson's r using the formula by Peterson and Brown [68]. Lastly, odds ratio (OR) and log odds ratio (L_{OR}) are converted using the formulae of Sánchez-Meca et al. [69]. Finally, a transformation (and back transformation) to Fisher's z (r_z) (and back to Pearson's r) is applied to correlation coefficients to stabilize the variance. To do so, it is used respectively the Fisher's z formula [70] and the inverse of the Fisher's z formula. Analyses are performed using the "metafor" package [71; v.4.4.0] for RStudio (v.4.3.3). In total, thirty-five possible predictors (i.e., Altruistic Values, Biospheric Values, Children, Climate Change Awareness, Conservative, Education, Egoistic Values, Event Perceived Likelihood, Expected Response Efficacy, Fatalism, Woman, Home Ownership, Household Size, Income, Knowledge, Married, Media Use, Negative Emotions, Objective Risk, Place Attachment, Preparedness, Prior Experience, Prior Experience Severity, Pro-Environmental Orientation [this variable was measured in all studies with the New Environmental Paradigm [72] scale], Psychological Distance, Religiosity, Residential Tenure, Self-efficacy in Response, Sense of Community, Social Norms, Social Support, Trust in Authorities, Trust in Community, Vulnerability) are identified.

Moreover, fourteen variables (i.e., Attribution of Responsibility, Big Five Personality Traits, Community Participation, Connectedness with Nature, Employment, Environmental Attitudes, Frequency of Information Exchange in the Social Network, Future Migration Probability, Locus of Control, Perceived Behavioral Control, Risk Salience, Risk Seeking, Rural or Urban Residential Location, Worldviews) are omitted because they do not reach the minimum of five studies required for conducting a meta-analysis. Table S2 lists all included and excluded variables, reporting merged/modified variable names, original variable names, conceptual definitions, and the respective number of records. Fig. 2 shows the number of studies for each variable, listed in order of magnitude, from the least to the most represented.

2.4. Heterogeneity analysis

Heterogeneity among studies is assessed using different statistics, namely Cochran's Q , σ^2 , and I^2 . Cochran's Q is a test that provides statistical significance of observed heterogeneity following a chi-square distribution [73]. This test is dependent on the number of studies; thus, it could not be employed to compare different meta-analyses [73]. Moreover, when the number of studies is low, this statistic may not have adequate power [70]. In addition, heterogeneity was partitioned into between- and within-study components, with separate estimates of σ^2 (level-specific variance) and I^2 (level-specific percentage of total variation) provided for each level. This allowed us to disentangle the sources of heterogeneity and better understand whether variability arose primarily across or within studies [66,74].

2.5. Variables merge

Variables coming from different studies have been merged, with the aim to collect as many predictors of risk perception as possible. In several cases, variables exhibit a similar meaning (especially when looking at the specific items and instruments used) although they had been named differently. Thus, these variables are grouped (or considered as dependent effect sizes, in the case of more variables coming from the same study) considering the similar shared meaning. This practice increased the accuracy of the meta-analyses. More information about the merged variables is reported in Table S2.

3. Results

3.1. Preliminary Analysis: Normality of Distribution

Complete lists of the final studies included and of the classification of studies for each antecedent are presented in Tables S3 and S4,

respectively. Before conducting each meta-analysis, the normality of the distribution of the effect sizes for each predictor variable is assessed. Values of skewness and kurtosis between -2 and $+2$ are considered acceptable. Table S5 presents the values of skewness and kurtosis for each identified predictor. Regarding three predictors, skewness and kurtosis show a non-normality distribution of effects, namely Age, Education, and Income. Values remain unacceptable also after removing outliers (See Paragraph S1 “Ancillary Analyses: Detection of Outliers” in the Supplementary Materials for an in-depth discussion of the detection of outliers). Thus, a violation of the assumption of normality of the distribution of the effect sizes for the meta-analysis is detected [75] and these three variables are omitted from further analysis.

3.2. Main results

Results are presented according to the two aims, namely: 1) to estimate effect sizes of different potential antecedents of risk perception in the domain of natural hazards (Effect Sizes Analysis); and 2) to investigate the effect of possible moderators of such relationships (Moderation Analysis).

3.2.1. Aim 1: Effect Sizes Analysis

Overall, 127 studies (121 records) are considered. Results of the multi-level meta-analyses for each antecedent are shown in Table 2 and are ordered by resulted effect size. Fig. 3 shows a graphical representation of the effects ordered by size. Specifically, Fig. 3 was generated in R (v. 4.3.3) using the *ggplot2* package. Two datasets are used: one containing the pooled meta-analytic estimates for each antecedent and their confidence intervals, and a second containing the individual effect sizes extracted from the primary studies. The figure is created by first plotting the pooled correlation coefficients (r) for each antecedent as point estimates and subsequently adding the corresponding 95% confidence intervals as error bars. Individual study effect sizes are then overlaid on the same graph as grey points. Point sizes are finally scaled to the sample size of the corresponding study to visually distinguish between larger and smaller samples.

As can be seen in Table 2, the effects of ten variables do not result significant, namely those of Social Support, Psychological Distance, Place Attachment, Children, Sense of Community, Religiosity, Married, Residential Tenure, Self-efficacy in Response, and

Table 2

Results of the multi-level meta-analyses showing estimated effects for each antecedent of risk perception. Variables are sorted by effect size ascending order, from negative to positive effect.

Variable	r	95% CI	k	m	n	Q	σ^2 (L2, L3)	I^2 (L2, L3)	p
Social Support	-0.18	-0.40-0.07	5	5	4961	226.05	NA, 0.04	NA, 48.76	.158
Conservative	-0.16	-0.26 to -0.06	15	17	13404	593.50	0.002, 0.04	5.58, 90.66	.002
Psychological Distance	-0.15	-0.53-0.27	5	12	1240	574.85	0.05, 0.21	19.03, 79.37	.482
Place Attachment	-0.11	-0.39-0.20	7	7	3858	180.07	NA, 0.08	NA, 49.03	.498
Children	-0.09	-0.23-0.06	7	8	4674	117.32	0.00, 0.04	0.00, 95.18	.258
Fatalism	-0.07	-0.15-0.005	5	5	3260	15.69	NA, 0.003	NA, 37.15	.069
Sense of Community	-0.05	-0.20-0.11	6	6	2821	59.80	NA, 0.02	NA, 45.45	.551
Religiosity	-0.03	-0.14-0.08	9	10	34549	436.42	0.00, 0.03	0.00, 95.86	.543
Married	-0.01	-0.12-0.10	5	5	2258	20.19	NA, 0.006	NA, 37.85	.877
Residential Tenure	0.002	-0.06-0.06	14	18	8193	107.65	0.001, 0.01	7.34, 69.93	.943
Self-efficacy in Response	0.05	-0.11-0.20	14	14	9364	679.04	NA, 0.04	NA, 48.07	.541
Household Size	0.06	0.01-0.10	8	8	5053	12.41	NA, 0.00	NA, 15.63	.012
Home Ownership	0.08	-0.01-0.16	8	8	3272	38.79	NA, 0.006	NA, 38.90	.074
Trust in Community	0.09	-0.07-0.24	6	8	3894	159.16	0.001, 0.04	3.25, 91.24	.291
Woman	0.09	0.05-0.13	54	56	64943	893.61	0.01, 0.01	28.27, 58.77	<.0001
Objective Risk	0.1	0.02-0.17	12	14	6117	162.19	0.001, 0.02	7.11, 79.78	.012
Media Use	0.12	0.01-0.22	8	15	31878	193.41	0.001, 0.02	4.23, 87.81	.03
Egoistic Values	0.16	0.08-0.24	7	7	4280	45.58	NA, 0.005	NA, 41.70	.0001
Prior Experience	0.16	0.09-0.24	32	35	22459	921.35	0.05, 0.00	94.73, 0.00	<.0001
Prior Experience Severity	0.17	0.07-0.27	10	12	8268	75.89	0.00, 0.03	0.00, 90.51	.001
Preparedness	0.18	0.12-0.24	16	20	9870	212.58	0.00, 0.01	0.00, 82.05	<.0001
Knowledge	0.19	0.14-0.24	33	47	24012	1627.22	0.03, 0.00	93.53, 0.00	<.0001
Trust in Authorities	0.20	0.03-0.36	14	19	13885	1444.39	0.00, 0.11	0.00, 98.73	.019
Vulnerability	0.22	0.13-0.31	6	6	5684	78.46	NA, 0.006	NA, 42.13	<.0001
Expected Response Efficacy	0.30	0.05-0.51	7	7	4359	402.59	NA, 0.06	NA, 48.20	.02
Event Perceived Likelihood	0.36	0.12-0.55	10	10	5510	1222.12	NA, 0.08	NA, 48.86	.004
Social Norms	0.36	0.25-0.45	13	16	10897	618.30	0.02, 0.02	50.45, 45.59	<.0001
Altruistic Values	0.40	0.32-0.47	7	7	4280	50.35	NA, 0.006	NA, 42.65	<.0001
Negative Emotions	0.46	0.37-0.54	27	32	27722	2025.45	0.002, 0.08	1.95, 95.12	<.0001
Biospheric Values	0.48	0.39-0.56	7	7	4280	80.76	NA, 0.009	NA, 44.74	<.0001
Climate Change Awareness	0.50	0.32-0.65	14	16	12236	2279.12	0.03, 0.15	14.11, 84.30	<.0001
Pro-Environmental Orientation	0.53	0.32-0.69	5	5	2661	85.77	NA, 0.04	NA, 47.77	<.0001

Note. K = number of studies included in the meta-analysis; m = number of effect sizes included in the meta-analysis; n = total number of participants across all the studies included in each meta-analysis; Q = total heterogeneity observed in the analysis; σ^2 (L2,L3) = estimated variance at Level 2 (within studies) and Level 3 (between studies); I^2 (L2,L3) = proportion of heterogeneity at Level 2 and Level 3.

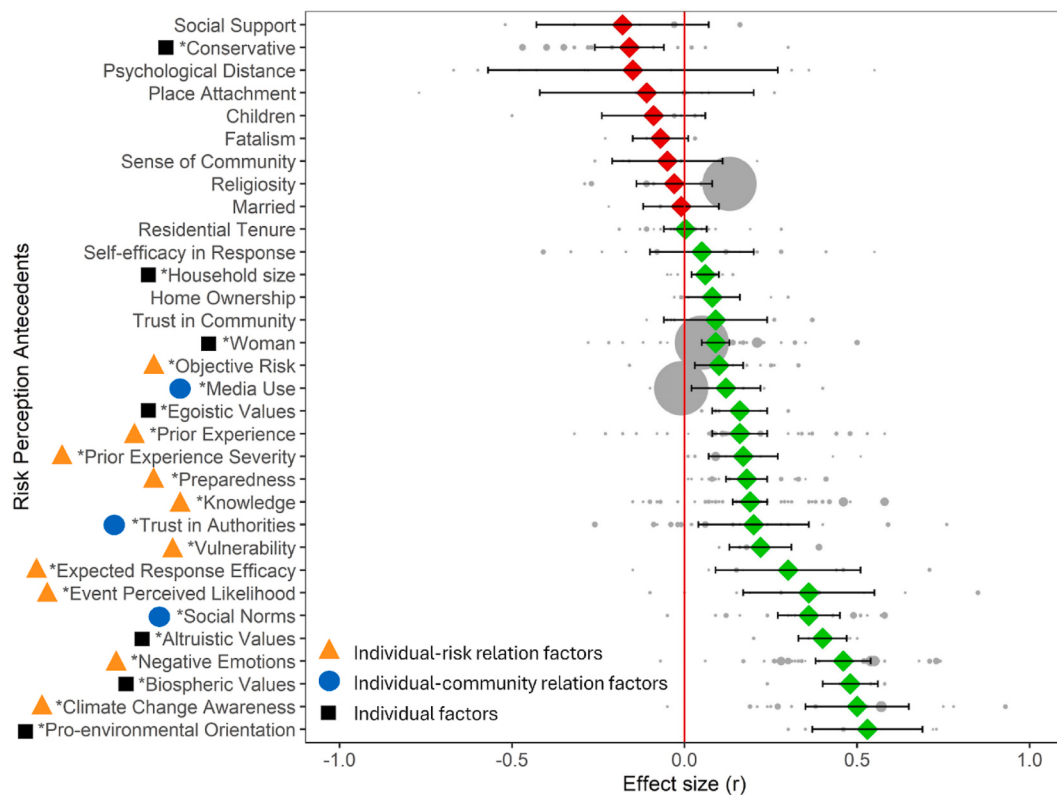


Fig. 3. Graphical representation of mean estimated effects for the antecedents of risk perception

Note. Red diamonds indicate negative meta-analytical effect sizes (r) for each specific variable. Green diamonds indicate positive meta-analytical effect sizes (r) for each specific variable. Error bars represent 95% confidence intervals (CI). The red line indicates the zero. Confidence intervals that include the zero (error bars that cross the red line) indicate non-significant effect sizes (i.e., Social Support, Psychological Distance, Place Attachment, Children, Fatalism, Sense of Community, Religiosity, Married, Residential Tenure, Self-efficacy in Response, Home Ownership, and Trust in Community). Variables names marked with an asterisk indicate significant effect sizes for that antecedent. Each grey circle represents the single effect size observed in each individual study included in each meta-analysis, while the size of each circle represents the sample size of the respective study.

Trust in Community. The effects of two variables, namely Fatalism (negative effect) and Home Ownership (positive effect), show a tendency to significance. Significant mean correlation effect sizes are then interpreted following the recommendations from Lovakov & Agadullina [76]: $r = .12$ represents a small, $r = .24$ a medium, and $r = .41$ a large effect. Twelve variables result in small effect sizes, namely, Conservative, Household size, Woman, Objective Risk, Media Use, Egoistic Values, Prior Experience, Prior Experience Severity, Preparedness, Knowledge, Trust in Authorities, and Vulnerability. Four variables show medium effect sizes, namely Expected Response Efficacy, Social Norms, Event Perceived Likelihood, and Altruistic Values. Lastly, four variables show large effect sizes, namely Negative Emotions, Biospheric Values, Climate Change Awareness, and Pro-Environmental Orientation.

Fig. 4 presents, for each antecedent, the number of studies that assess risk perception for each type of natural hazard. This figure is manually constructed from a contingency table reporting the frequency of studies for each combination of antecedent and natural hazard type. Frequencies are first tabulated from the study database and then arranged in a matrix, with antecedents represented by rows and hazard categories by columns.

Overall, in the included studies, perceived risk is assessed regarding twelve natural hazards and multi-risk hazards. **Fig. 4** shows how the literature on the topic focuses mainly on some specific natural hazards, while others are underrepresented. Specifically, the risk perception of earthquakes, floods, cyclones, and climate change seems overrepresented; while on the other hand, other natural hazards, such as landslides, drought, heat waves, or biodiversity loss turn out to be poorly investigated when not totally overlooked in the literature.

3.2.1.1. Publication bias. Publication bias occurs whenever published research is systematically unrepresentative of the population of studies done on a specific topic [77]. This may take place due to the tendency to publish statistically significant results more than non-significant ones, leading to biased meta-analyses and inflated estimates [78]. To evaluate the presence of publication bias, the Egger's regression test of funnel plot asymmetry [79,80] is considered. See [Table S6](#) for the analysis results for the assessment of publication bias.

As can be seen in [Table S6](#), the Egger's regression test is significant for seven predictors, namely Conservative, Fatalism, Trust in

	Earthquake	Vulcanic activity	Landslide	Flood	Tsunami	Cyclone	Wildfire	Drought	Sea level rise	Heat wave	Biodiversity loss	Climate change	Multi-risk	Total
Social Support	1	0	0	2	0	0	0	0	0	0	0	1	1	5
Conservative	1	0	0	0	0	0	0	0	1	0	0	12	1	15
Psychological Distance	0	0	0	1	0	0	0	1	0	0	0	2	1	5
Place Attachment	0	0	0	3	1	1	1	0	0	0	0	0	1	7
Children	2	0	0	2	0	2	0	0	1	0	0	0	0	7
Fatalism	2	0	0	3	0	0	0	0	0	0	0	0	0	5
Sense of Community	0	1	0	3	0	1	0	0	0	0	0	0	1	6
Religiosity	1	0	0	0	0	0	0	0	0	0	0	6	2	9
Married	2	0	0	2	0	0	0	0	0	0	0	1	0	5
Residential Tenure	3	0	0	4	2	1	0	0	0	0	0	1	3	14
Self-efficacy in Response	1	2	0	1	1	0	2	0	0	0	0	4	3	14
Household size	0	2	0	3	2	0	0	0	0	0	0	1	0	8
Home Ownership	4	0	0	2	1	0	0	0	1	0	0	0	0	8
Trust in Community	3	0	0	1	0	0	0	0	0	0	0	1	1	6
Woman	7	2	0	9	2	5	0	0	1	1	0	22	5	54
Objective Risk	2	1	0	4	2	0	0	0	1	0	0	2	0	12
Media Use	1	0	0	0	0	1	0	0	1	0	0	4	1	8
Egocistic Values	0	0	0	0	0	0	0	0	0	0	0	7	0	7
Prior Experience	2	1	1	11	2	3	1	0	0	0	0	8	3	32
Prior Experience Severity	4	0	0	2	0	2	0	0	0	0	0	1	1	10
Preparedness	3	1	1	4	1	1	1	0	0	0	0	1	3	16
Trust in Authorities	1	1	0	2	0	1	1	0	0	0	0	5	3	15
Knowledge	5	1	1	4	3	0	0	0	0	2	1	13	3	33
Vulnerability	1	2	0	1	1	1	0	0	0	0	0	0	0	6
Expected Response Efficacy	1	1	0	0	0	1	0	0	0	0	0	3	1	7
Social Norms	2	0	0	1	0	0	0	0	0	0	0	9	1	13
Event Perceived Likelihood	2	0	0	2	1	1	1	0	0	0	0	2	1	10
Altruistic Values	0	0	0	0	0	0	0	0	0	0	0	7	0	7
Negative Emotions	2	1	0	7	0	1	0	0	0	0	1	12	3	27
Biospheric Values	0	0	0	0	0	0	0	0	0	0	0	7	0	7
Climate Change Awareness	0	0	0	0	0	2	0	0	0	0	0	11	1	14
Pro-environmental Orientation	0	0	0	0	0	0	0	0	0	0	0	4	1	5

Fig. 4. Contingency table showing the frequencies of the type of risk assessed per antecedent considered

Note. The column “Cyclone” includes hurricanes, tornadoes, and typhoons. The columns of other three expected types of natural hazards (namely, storm, thunder lightning, and ocean acidification) were removed since no studies were found for them. Studies in the column “Climate change” investigated more than one natural hazard considered as an effect of climate change or climate change in general. The red color highlights zero studies in that specific variable for that specific natural hazard. The yellow color emphasizes one to four studies in that specific variable for that specific natural hazard. The green color indicates at least five studies in that specific variable for that specific natural hazard. The green color also shows that an adequate number of studies are available to conduct a specific meta-analysis in that specific variable for that specific natural hazard.

Community, Prior Experience Severity, Preparedness, Knowledge, and Pro-Environmental Orientation. All in all, there is small evidence that publication bias affects the effect sizes resulting from the analyses.

3.2.2. Aim 2: moderation analysis

Moderation analyses are generally conducted in meta-analyses to interpret heterogeneity across studies [81]. In our case, the results of most of the conducted meta-analyses showed considerable heterogeneity among effect sizes reported by each included individual study (see Table 2, indices I^2 , Q , and σ^2). To detect possible sources of heterogeneity, different moderator variables are hypothesized.

Such moderators have been picked up because they vary across the included studies and/or because they do not reach the threshold to be included as predictors ($k \geq 5$) and/or because they represent inter-study methodological differences theoretically bearing potential effects. Some moderators are considered across all variables, while others are hypothesized only for specific variables.

Specifically, the moderators hypothesized for all the variables are: case study (n/y); type of natural hazard (Climate change/Other); rural/urban sample; low/high risk area sample; age; gender.

Moderators hypothesized for specific variables are: residential tenure referring to Area/Home (variable: Residential tenure); measurement referring to having or not experienced/Frequency of experience of a specific natural hazard (variable: Prior Experience); type of knowledge (i.e., Objective knowledge/Subjective knowledge; variable: Knowledge); type of social norms (i.e., Descriptive/Injunctive; variable: Social norms).

Hypothesized moderators are tested only on significant effect-size meta-analyses. However, despite the hypotheses, in practice it is not always possible to test the identified moderators since not for every antecedent variable the minimum number of studies required for moderation analyses is reached. Indeed, studies reporting information on the moderator variables need to be a minimum of 6 studies for each continuous moderator (in our case, Age), and a minimum of 4 studies for each level of a categorical moderator [82]. Some moderators are never tested since they never reach the above-mentioned thresholds: grey literature (n/y); type of risk (health, economic); risk attribution (to self/others); education.

Considering the moderator “type of natural hazard”, the choice of categories was forced by the number of studies for each moderator category. In fact, regarding the moderator “Type of natural hazard”, the categories “Climate change” and “Other” were developed, as the natural hazard “climate change” is overrepresented compared to the other natural hazards (none of which reached such a large number of studies to be considered as a category itself). For climate change, all those phenomena related to climate change that are not strictly related to specific natural hazards are considered. In the studies analyzed, risk perception indeed referred simply to climate change as a phenomenon in its own right. Moderation analyses hypothesized for all variables are reported in Table S7, while those hypothesized for specific variables are reported in Table 3.

The Risk area of the sample is significant in two cases (see Table S7). First, it moderates the effect of Woman: Indeed, it seems that when the Risk area is high, there is no difference between women and men, while when the Risk is low, women perceive more risk. Moreover, the Risk area of the sample moderates the effect of Negative Emotions: in low and high Risk areas, Negative Emotions positively predict Risk Perception, with a largest effect for the former area. Regarding specific moderators (see Table 3), it resulted that the Measurement of prior experience (Having experience/Frequency of the experience) does not matter in predicting Risk Perception, while both Descriptive and Injunctive Social Norms have a positive effect on Risk Perception, with the latter demonstrating a larger effect. There is no difference in Objective and Subjective Knowledge in predicting Risk Perception. Lastly, no effects were found for the moderators: Case study, Rural/urban sample, Age, and Gender.

4. Discussion

First, the discussion of the results is presented; then, some tentative implications are advanced for both scientific research and applied purposes.

4.1. Discussion of the findings

The aim of the current work is twofold. The first aim is to identify the antecedents of risk perception in different natural hazards, while the second is to find moderators of the resulting relationships, and their relevance both in theoretical terms and for methodological implications. Regarding the first aim, a series of thirty-two meta-analyses show significant relationships with most of the predictors that emerged from the literature. In particular, these resulted in antecedents tapping the clusters identified by Bonaiuto and Ariccio [45]. Table 4 shows a classification of all the resulting antecedents by cluster and the strength of their respective effects.

As can be seen, the strongest effects (greater than or equal to .24, i.e., medium to large effect sizes) regarding the first cluster, namely the factors concerning the relationship between the individual and the risk, emerge for the variables Climate Change Awareness, Negative Emotions, Event Perceived Likelihood, and Expected Response Efficacy. The strongest effects regarding the second cluster, namely the variables related to the relationship between the individual and the community, are observed for Social Norms. Lastly, the largest effects for the third cluster, namely individual factors, are observed for Pro-Environmental Orientation and Individual Values (i.e., Biospheric and Altruistic).

All in all, it seems that the cluster with the majority of variables showing the strongest effects is the first one (factors concerning the relationship between the individual and the risk). Regarding individual factors, only dispositional factors exhibit strong effects; in fact, regarding the other factors included in this cluster, namely the sociodemographic factors, no variable exhibited medium to large effects and, thus, this suggests that they are less important antecedents. Overall, the findings are partly in line with the recent meta-analysis by van Valkengoed and Steg [8] on predicting adaptation behaviors to climate changes, especially regarding medium effects observed for Expected Response Efficacy and Social Norms, and the significant role (although with different magnitudes) of Climate Change Awareness, Knowledge, Prior Experience, and Trust in Authorities. Interestingly, both Previous Experience and Trust in Authorities – although emerged as the two most important antecedents in the analysis by Wachinger et al. [10] – do not exhibit the strongest effects according to our findings.

The current work gives back a quantitative summary of the effects reported in the literature that helps to answer questions raised by previous reviews. For instance, it emerges that Prior Experience and Prior Experience Severity exhibit the exact same positive effect, contrary to what was hypothesized by Wachinger et al. [10]. Indeed, they expected that it is the severity of the experience to affect risk perception, more than the experience itself. These meta-analyses show that both aspects of experience play a similar, important role. Moreover, the effect of Trust in Authorities resulted positive, thus questioning the suggested argument by which more devoted citizens trust authorities to carry the responsibility for risk, diminishing their risk perception (see [10]). This result may rather suggest the opposite, namely that relying on authorities may somewhat transfer knowledge from the experts to the lay citizen, ameliorating the efficiency of risk communication, and ultimately filling the gap between the objective and subjective risk [10].

The strength of the effects of sociodemographic variables, including gender, which were found inconsistent across reviews and by some authors [10,19,32], result weak (Gender, Conservative, Household Size), with some variables showing non-significant results (Children, Religiosity, Married, Residential Tenure, and Home Ownership). Lastly, the role of other antecedents, including more

Table 3

Results of the multi-level moderation analyses conducted on the relationships between different antecedents of risk perception and risk perception and hypothesized for specific variables.

Antecedents of risk perception	<i>r</i>	<i>p</i>	σ_{BTW}^2	σ_{WITH}^2
Prior Experience				
Moderator: Y/N, Frequency		0.257	0.00	NA
Knowledge				
Moderator: Type of knowledge		0.513	0.00	0.03
Social Norms				
Moderator: Descriptive/Injunctive*		0.001	0.003	0.05
Descriptive Norms	0.26***		.0002	
Injunctive Norms	0.42***		<.0001	

Note. *** $p < .001$; ** $p < .01$; * $p < .05$.

Table 4

Classification of resulting antecedents of risk perception by cluster and strength of their effect.

Antecedents		Effects			
		Small	Medium	Large	Non-significant
Factors concerning the relationship between the individual and the risk		Objective Risk (+) Prior Experience (+) Prior Experience Severity (+) Preparedness (+) Knowledge (+) Vulnerability (+)	Expected Response Efficacy (+) Event Perceived Likelihood (+)	Negative Emotions (+) Climate Change Awareness (+)	Psychological Distance (–)
Factors concerning the relationship between the individual and the community		Media Use (+) Trust in Authorities (+)	Social Norms (+)		Social Support (–) Place Attachment (–) Sense of Community (–) Trust in Community (+) Children (–) Religiosity (–) Married (–) Residential Tenure (+) Home Ownership (+) Fatalism (–) Self-efficacy in Response (+)
Individual factors	Sociodemographic factors	Conservative (–) Household Size (+) Woman (+)			
	Dispositional factors	Egoistic Values (+)	Altruistic Values (+)	Biospheric Values (+) Pro-Environmental Orientation (+)	

Note. (+): positive effect; (–): negative effect. The effects of Home Ownership and Fatalism were marginally significant ($.05 < p < .10$). According to [76], effect sizes are interpreted as follows. Small: $0.0 < r < 0.24$; Medium: $0.24 \leq r < 0.41$; Large: $r \geq 0.41$. Variables in each cell are listed by effect size (from the smallest to the largest).

traditional environmental psychology variables, was better outlined, with some significant and non-significant effects.

Regarding significant findings for the factors concerning the relationship between the individual and the risk, higher Objective risk and Knowledge were confirmed to enhance risk perception as previously found [10,19,43], while for mountain hazards results were found inconsistent [32]. With no surprise, Vulnerability, Event Perceived Likelihood, and Negative Emotions - all treated as independent variables, considering the correlational nature of the meta-analyses (based on Pearson's correlations) - were all positively associated with risk perception, as they were previously considered as different aspects of the same construct (e.g., [30]). Preparedness, namely protective behaviors adopted before the hazard, was positively associated with risk perception. This result is difficult to interpret: One may expect that having implemented protective measures may decrease risk perception. Indeed, people may be motivated to adopt protective measures to decrease their risk perception ([31,83]; for a more detailed discussion see [43]). Nevertheless, this can be true for different aspects of risk perception not investigated here, such as vulnerability and negative emotions (e.g., worry). In our case, it can be that preparedness behaviors may enhance risk salience, thus heightening risk perception (and severity of the consequences). In any case, although these findings are cross-sectional, they may suggest a bidirectional relationship between preparedness and risk perception, which is not usually contemplated by classic theories focused on explaining preparedness and response behaviors, such as the Protection Motivation Theory [25] and the Protective Action Decision Model (PADM; [39]). In such frameworks, risk perception usually appears as a precursor of protective behavior, although several studies suggest that the contrary is also plausible [31,43,44]. Similarly, the positive and significant effect of Expected Response Efficacy, usually related to the motivation to engage in protective behaviors according to the Protection Motivation Theory [25], may be associated with higher risk salience. On the whole, these effects speak in favor of adopting appropriate preparedness measures to stay tuned on the risk by perceiving it.

Regarding significant findings for the factors concerning the relationship between the individual and the community, the Media Use intended to be informed about hazards enhances risk perception: This effect may pass through increased knowledge provided by the medium (e.g., [84]). As mentioned above, higher Trust in Authorities results associated with higher risk perception, suggesting that a good climate of trust with community leaders may efficiently convey the need for risk perception [85]. Similarly, the central role of social norms was highlighted by the study of Solberg et al. [44], which emphasizes the centrality of normative influence on the perception of natural hazards. Van Valkengoed & Steg [8] then highlighted how social norms predict adaptive behaviors. Considering risk perception as one of the main leverages toward adaptive behaviors [8], it appears consistent with the literature on how norms can also positively influence risk perception.

Lastly, regarding individual factors, it is interesting to note that all values considered here, namely Egoistic, Altruistic, and Biospheric, were found to enhance risk perception, with stronger effects for the last two. This suggests that having something to care about (whatever it is) may enhance risk salience and the worry that valuable aspects of life are at risk, i.e., a result in line with Vested Interest Theory studies on environmental risk coping [86,87]. Interestingly, the three most important predictors found across our meta-analysis were Biospheric Values, Climate Change Awareness, and Pro-Environmental Orientation. This poses the question of the importance of sensibility to the environment [88] and general environmental education [89].

Regarding non-significant findings, the results concerning the variables related to the sense of community and social support (i.e., Social Support, Sense of Community, and Trust in Community) could be interpreted as a confirmation of the theorization that in the

contexts of natural hazards, these do not play a protective role in a preparatory phase, as much as they act more in helping people to cope with natural hazards once the event has already occurred [90]. Thus, these variables are probably more related to processes involved in coping with past natural hazards than in preparing for or perceiving future natural hazards, in which risk perception plays a prominent role.

As for the lack of significance of variables Psychological Distance and Self-Efficacy in Response, this result is unexpected. Classical studies (e.g., [91]), indeed, revealed that lower psychological distance is associated with higher levels of uncertainty related to climate change and its consequences, which is strictly related to risk perception (see [92]). Nevertheless, it is possible that by converging studies that examined the role of Psychological Distance in different natural hazards, this effect is lost. Unfortunately, since studies were scanty for this antecedent and the result was non-significant, a further analysis per type of natural hazard was not possible. Regarding Self-Efficacy in Response, classic theories such as the Protection Motivation Theory [25] identify efficacy as a protective factor against the emotional aspect of risk perception of the hazard and the hazard itself. Other studies (e.g., [93]) have then shown that response efficacy predicts both emotional and cognitive aspects of risk perception. Thus, the lack of significance could be due to the large number of risks considered in our analysis. Perceiving self-efficacy in response to some types of risk (e.g., earthquakes) may have a greater impact on risk perception than, for example, in response to risks such as climate change, toward which it is difficult to perceive direct self-efficacy in response, and thus to consequentially have an impact on the subsequent risk perception. As with Psychological Distance, a further analysis per type of natural hazard was not possible. Future studies will therefore need to further investigate the relationship between these variables, to understand how and when they may impact the risk perception of natural hazards.

Regarding Place Attachment, its role in the face of natural hazards seems not to be associated with risk perception in most of the studies analyzed. This suggests that place attachment does not intervene in increasing risk perception as one may expect (e.g., [44, 94]), presumably guiding instead protective behaviors in the face of risks [17]. It is worthy remember however how the predicting role of place attachment has been reported to vary from positive to negative according to various features [15,95], such as the object of the attachment (residency or safety area; [96]) and the style of attachment (over and above its intensity; [97,98]). This means that the role of place attachment for risk perception still needs to be deeply considered by further future studies. Lastly, the role of Fatalism was dismissed by our results. Since fatalism beliefs are strictly connected to the degree of control attributed to the hazard [44], is it possible that, once again, the effect varies across different hazards, perceived as more (i.e., climate change) or less (e.g., earthquake, volcanic activity, floods) controllable by human action (see also [10]). This was not possible to test in our meta-analysis.

Although the findings are rich and deserve attention, it is important to highlight that several meta-analyses point to a certain degree of publication bias across different antecedents. This means that results regarding these antecedents should be interpreted with caution. Lastly, almost all meta-analyses show a high degree of heterogeneity among studies conducted. This points to a high dispersion of effect sizes among studies considered for each meta-analysis. One way to explain this heterogeneity is through the identification of moderators.

The second aim of this work is to find possible moderators of the identified relationship of each predictor with risk perception. The conducted moderation analyses showed important as well as non-significant moderators. Regarding the former, Low or high-risk area sample moderates the relationship between Woman and Risk perception, in a way that the effect is positive and significant only when the risk area of the sample is low. This means that women may better foresee risk when not immediately salient, while, when the risk is high, there is no such a difference between genders (for a theoretical and methodological perspective about gender differences in risk perception, see [99]). This result is interesting since the role of gender in previous literature was evaluated as inconsistent by some reviews [10,32]. Our findings highlight how the role of gender may differ conditional on the level of the risk area.

Moreover, the Type of social norm moderates the relationship between Social Norms and Risk Perception. It results that both Injunctive and Descriptive norms are positively associated with Risk Perception, but the effect is stronger for Injunctive norms contrary to the results by van Valkengoed and Steg [8]. This underscores a key distinction: while adaptive behaviors tend to be primarily guided by what others are doing, risk perception is more influenced by what others believe is the appropriate course of action in response to the hazard. This pattern aligns with the differing motivational functions of social norms. Descriptive norms convey information about effective behavior in a given context, whereas injunctive norms reflect socially shared expectations often tied to cognitive and affective judgments [100–102], including risk perception. Lastly, the Low or High risk area of the sample reported a significant effect in the relationship between Negative emotions and Risk perception. It emerges that Low risk area samples had a higher effect as compared to High risk area samples. This result suggests that negative emotions are more effective in shaping risk perception when the risk in the area is low (vs. high). It is possible that emotions are less important where the risk is better known. In fact, it is plausible that people living in a high-risk area have already experienced a natural event and are, consequently, basing their risk perceptions on other aspects (e.g., consequences); however, this speculation requires further studies.

Of note are also the non-significant effects of the moderators Case study, Rural/urban sample, Age, and Gender, which strengthen the importance of the observed relationships. Moreover, the moderation analysis also shows that the Measurement of Prior Experience (i.e., having or not experienced vs. frequency of experience) does not affect the relationship between this antecedent and risk perception, in line with the result of the meta-analysis by van Valkengoed and Steg [8]. Similarly, for Knowledge, the Type of knowledge (i.e., objective or subjective) does not affect the relationship between the antecedent Knowledge and Risk Perception (i.e., both types of knowledge equally work).

4.2. Strengths and limitations

This contribution represents a novel attempt to quantitatively summarize the available literature on the topic of the determinants of

risk perception. Some strengths of the work lie in the broad inclusiveness of records that allowed us to consider interdisciplinary studies, including also grey literature, and with no limits in terms of authors' countries (contrary to the review by Wachinger et al., which focused only on European research). This research is not free of limitations either. One of the most important is the choice regarding the measurement of risk perception for a study to be included in the meta-analyses, with the consequence of having excluded different conceptualizations of risk perception. This may have also been reflected in the results. As reported elsewhere [33], risk perception has been measured in different ways. Moreover, as egregiously expounded by Slovic and colleagues [103], when referring to perceived risk, "no one definition is correct, or suitable, for all problems" ([103], p. 21). Meta-analyses considering the antecedents of different, more specific, aspects of risk perception, such as event perceived likelihood and risk salience, or even considering both general holistic measurement of risk perception and severity of consequences alone, indeed, may give somewhat different results. Although our inclusion strategy was designed to maximize conceptual coherence, comparability across studies may be only partial, and some of the heterogeneity observed in the meta-analyses may reflect differences in the underlying conceptualization of the outcome variable rather than genuine differences in the relationships between antecedents and risk perception. This issue is not unique to the present study but reflects a longstanding challenge in risk perception research, where a widely shared operational definition is still lacking [33,103]. Future research would benefit from greater conceptual and measurement standardization and from reporting different dimensions of risk perception separately, which would allow future meta-analyses to investigate their potentially distinct antecedents.

A similar limitation concerns the heterogeneity of independent variable measurements. Although we grouped only conceptually similar variables under the same construct (see Table S2), variation in how these constructs were operationalized across studies remains, potentially affecting interpretability. While using only identical measures would reduce this issue, it would also drastically limit the number of eligible studies. Future meta-analyses could address this by coding measurement features in more detail or running subgroup analyses when feasible. Similarly, primary studies should prioritize shared definitions and validated instruments to enhance comparability. Otherwise, researchers with similar aims will likely encounter the same methodological challenges, as also noted in prior studies (e.g., [8,104]).

As mentioned in the Results section (see Fig. 4), research is scanty regarding some types of natural hazards (e.g., landslides, drought, heat waves, biodiversity loss) across all the variables here considered. Although our research considers a large number of studies analyzing different natural hazards, the overestimation of some hazards (e.g., climate change or flood) compared with others (e.g., drought) leads to reduced generalizability of these results and a call for higher hazard variety in future research. Hazards may be very different: e.g., the occurrence of some hazards is more abrupt with immediate and direct damages and casualties (e.g., earthquakes, cyclones), while the consequences of other hazards are only visible in the long term, with no less disastrous outcomes (e.g., sea level rise, loss of biodiversity; [55]). Therefore, broader research is needed to collect more data and to deepen the investigation of the antecedents of risk perception regarding these specific natural hazards.

Furthermore, the literature search highlights that the findings on the topic should be broadened (see Method). In fact, fourteen variables are found not reaching the minimum of five studies required for conducting a meta-analysis. Thus, more research is needed to allow a quantitative summary of the available results by including such variables too.

Finally, although in most of the analyzed studies the conceptual direction of the relationships was the same as presented in our meta-analyses (i.e., with risk perception as the outcome), it is essential to acknowledge that the correlational nature of the data (based on Pearson's r) limits any claims of causality. The meta-analytical estimates reported inherit the limitations of the original studies, including common method variance and the inability to establish directions of the observed effects among variables. Although meta-analysis increases statistical power and provides more robust estimates of associations, it cannot overcome limitations embedded in the primary data on which it is based [70]. For these reasons, without experimental manipulation, some observed associations may therefore reflect the influence of unmeasured covariates, mediators, or moderators, or bidirectional relationships (an inherent challenge in social science literature; [105]). Future research, including experimental designs and a more defined theoretical conceptualization, is needed to clarify the directionality of these effects and strengthen causal inferences. Moreover, the correlational nature of the data does not allow for a differentiation between influencing factors or co-variants (e.g., climate change awareness may not directly influence risk perception and could be influenced by the same factors as risk perception). Furthermore, some meta-analyses were conducted on relatively few studies, reflecting the current state of the literature. While all analyses met the a priori minimum inclusion criteria, effect size estimates and heterogeneity parameters derived from a limited number of studies should be interpreted with caution. Future research should prioritize both replication and the accumulation of evidence on under-investigated antecedents of risk perception.

Lastly, we should acknowledge that aggregating findings from samples with different characteristics may influence the results. Thus, whenever possible, we controlled for these differences through the use of moderators. Nevertheless, this has not always been possible on the basis of the selected studies (e.g., for Home Ownership, in most studies there were aggregated data of property owners and non-property owners).

Moreover, despite the adoption of multilevel meta-analytic models to account for dependencies among effect sizes, residual heterogeneity remained substantial across several antecedents. This suggests that additional study-level characteristics, not consistently reported in the primary literature and therefore impossible to code, may contribute to variability in the observed effects. As a consequence, some sources of heterogeneity may remain unexplained, and the reported average effect sizes should be interpreted as summary estimates that may vary across contexts, populations, and hazard types.

4.3. Implications for future research and theory

Although the results of the meta-analyses presented here help to answer questions raised in the literature, at the same time, they open new research pathways. More specifically, the relationships between some antecedents and risk perception deserve further investigation. For instance, the results highlight how a higher frequency of exposure to media that deals with specific natural hazards is associated with greater risk perception. Future studies may delve into this relationship, by investigating which type of communication has proved to be more effective, as well as the preferable media source. This research may provide important guidelines for policy-makers interested in enhancing awareness regarding specific risks associated with natural hazards.

Centrally, one of the insights from this meta-analysis should be to encourage scholars to use clearer measurements of risk perception, possibly avoiding unidimensional scores that may be difficult to compare across studies. Importantly, we believe that in studies on risk perception, unpacking the construct into different aspects (e.g., holistic risk perception, severity of consequences, probability, vulnerability, negative emotions; [30]; see also [106]) would allow future meta-analyses to specifically focus on the potentially different roles that the antecedents may play on distinct aspects of risk perception (e.g., see the discussion regarding the effect of Preparedness in the paragraph “4.1 Discussion of the Findings”). This should lead to a more complete picture of risk perception antecedents and more precise indications for action.

Lastly, as mentioned before, as far as we know, there are no previous theories that systematically address the specific role of each antecedent of risk perception on risk perception itself. Our findings offer some insights into the (crucial) development of future reasoning and expose the need for a conceptual effort in this direction. First, from a comparison between Table 1, which synthesizes the importance attributed to antecedents found in the literature by cluster, and Table 4, which offers a classification of resulting antecedents of risk perception by cluster and strength of their effect, we observe a general convergence on the identification of some factors (e.g., Preparedness, Knowledge). Nevertheless, findings suggest that the importance attributed by the literature to some antecedents (e.g., Prior Experience, Trust in Authorities) was overestimated, while for others (e.g., Event Perceived Likelihood) it was underestimated. Future theorizations may start from these findings to redefine how risk perception is shaped. For instance, it seems that factors concerning the relationship between the individual and the risk play a primary role in the formation of such perception. In particular, among all the antecedents in this cluster, affective factors (i.e., Negative Emotion) seem to play a larger role than some cognitive factors (e.g., Knowledge). Dispositional antecedents are also identified as strong predictors of risk perception (e.g., Biospheric Values, Pro-Environmental Orientation), while social and contextual variables (e.g., Social Support, Residential Tenure, Household Size) seem to play a weaker or non-significant role.

Importantly, based on our findings, future theorizing should consider the specificity of each hazard in defining these relationships, such as the type of hazard, and the level of risk in the focal area. Lastly, these findings could extend existing theories that considered the role of risk perception for the engagement in protective behaviors. In fact, considering that risk perception is mostly seen as an antecedent of protective behaviors from classic and widely used theories (e.g., the Protection Motivation Theory; [25]), identifying the antecedents of risk perception could mean widening the range of intervention. Specifically, if these findings are confirmed by future studies, classical theories may more closely consider that we can intervene on risk perception antecedents (e.g., Negative Emotions, Prior Experience, Trust in Authorities, Social Norms) to indirectly promote protective behaviors. Importantly, the population characteristics which can contribute to sustain the intervention, such as gender and personal values, need to be taken into consideration too.

5. Conclusion

The findings reported here are summed in Table 4 and may guide decision-makers and policymakers in enhancing awareness of risk especially, but not limited to, high-risk populations. In particular, risk management should consider the three clusters of antecedents and intervene accordingly to the specific phase in which risk perception proved to be essential, namely preparedness, response, and recovery.

Regarding the factors concerning the relationship between the individual and the risk, knowledge may be favored through media and education (e.g., [107]). Moreover, personal prior experience may be prompted through simulations that may show to the participants their possible risk through direct training [45]. The required timeframe of exposure could be estimated as short-medium time, under appropriate circumstances, with the necessity of a long-term frame for more stable and durable effects.

Implications at the societal level are envisaged in the second cluster, namely the factors concerning the relationship between the individual and the social community. Importantly, community interventions may consider the power of descriptive and injunctive norms in sustaining risk perception, that is, evidence from consensual behaviors respectively suggested (injunctive norms) as well as adopted (descriptive norms) by significant others. This may be used, for example, in advertisements as well as on social media and media in general [108]. Trust in authorities may be favored through direct dialogue with institutions, and leaders more attentive to the needs of the population.

Lastly, as highlighted also by Bonaiuto and Aricchio [45], individual factors may be more difficult to address because they are less easy to change. Fortunately, regarding socio-demographic factors, what emerged is also that these variables are not so important as compared to the other clusters. Both socio-demographic and dispositional factors resulting from the meta-analyses may be taken into consideration when designing educational, informational, and community interventions, to tailor specific actions for different individuals' categories. Interestingly, it seems that, among the most important dispositional determinants, there are people's values, which are relatively stable individual dispositions. It seems that all values (whether biospheric and altruistic ones as expected, or egoistic ones too) can play an important positive role here, in the sense that any target (either the environment, other persons, or the

person's interests), which is endowed with subjective importance, can work as a trigger for enhancing risk perceptions (and consequently protection behaviors) from people who assign importance to that target. This may entail considering the importance given to different targets by different cultures and micro-cultures. Interventions should be fueled by continuous research and vice versa, to more deeply understand how to encourage protective actions by specific populations and constantly ameliorate field interventions. There are in fact already some pieces of evidence that speak in favor of adapting information and communication addressed to the inhabitants of flood risk areas by targeting their personal involvement in the consequences (e.g., by using the Vested Interest Theory; [86,87]).

In conclusion, advancements in the study of the antecedents of risk perception are needed. High risk perception has been found to be an important motivational factor for individuals in taking action to protect themselves from a natural hazard [8]. Nevertheless, the relationship between risk perception and behavior is not always straightforward [96]. In fact, scholars have been referring to a “risk perception paradox” for which high perceived risk can be not associated, or even negatively associated, with protective behavior, both before, during, and after the event [10]. Studying the antecedents of risk perception is important to shed light on the mechanisms underlying it and to intervene in altering risk perception to favor protective behavior. Ultimately, these findings expose the importance of the future development of a more comprehensive theoretical framework on the formation of risk perception in natural hazards, which represents a crucial asset for individuals and communities coping with natural hazards (whether climate change induced or not).

Author note

The presented work is part of the RETURN Extended Partnership being based on its deliverable DV5.1 dated 30.11.2023. Specifically, the Authors acknowledge the research funding PE PNRR “RETURN – Multi-Risk Science for Resilient Communities Under a Changing Climate” for Task 7.5.1 – Measuring the gap between objective risk and perceived risk, Work Package WP7.5 - Psychological, sociological and behavioral aspects in decision making and in risk communication, within Spoke 7 – project TS3– Communities’ resilience to risks: social, economic, legal and cultural dimensions (Spoke: UNIFI Supported by CIMA Research Foundation; Spoke Coordinators: Fabio Castelli, Marina Morando, Nicola Rebora), funding from the European Union Next-GenerationEU (National Recovery and Resilience Plan – NRRP, Mission 4, Component 2, Investment 1.3 – D.D. 1243 2/8/2022, PE0000005, CUP: B53C2200402002). We have no known conflict of interest to disclose.

CRedit authorship contribution statement

Annalisa Theodorou: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Alessandro Milani:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Federica Dessi:** Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Mei Xie:** Data curation, Investigation. **Marino Bonaiuto:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Marino Bonaiuto reports financial support was provided by European Union. If there are other authors, they 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.2026.106281>.

Data availability

Data will be made available on request.

References

- [1] Pliny the Elder. (78 C.E.). *Historia Naturalis*. Venice, Johannes de Spira, 1469.
- [2] IPCC, Summary for policymakers, in: H. Lee, J. Romero (Eds.), *Core Writing Team, Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, IPCC, Geneva, Switzerland, 2023, pp. 1–34, <https://doi.org/10.59327/IPCC/AR6-9789291691647.001>.
- [3] UNDRR, *Hyogo framework for action 2005-2015: building the resilience of nations and communities to disasters*. <https://www.refworld.org/docid/42b98a704.html>, 2005.
- [4] UNDRR, *Report of the open-ended Intergovernmental Expert Working Group on Indicators and Terminology Relating to Disaster Risk Reduction*, 2016.
- [5] H. Ritchie, P. Rosado, M. Roser, *Natural disasters*. <https://ourworldindata.org/natural-disasters>, 2022.

- [6] UNDRR, Sendai framework for disaster risk reduction 2015-2030. <https://www.unisdr.org/we/inform/publications/43291>, 2015.
- [7] P. Slovic, Perception of risk, *Science* 236 (4799) (1987) 280–285, <https://doi.org/10.1126/science.3563507>.
- [8] A.M. van Valkengoed, L. Steg, Meta-analyses of factors motivating climate change adaptation behaviour, *Nat. Clim. Change* 9 (2) (2019) 158–163, <https://doi.org/10.1038/s41558-018-0371-y>.
- [9] T. Schmitt, J. Eisenberg, R.R. Rao (Eds.), *Improving Disaster Management: the Role of IT in Mitigation, Preparedness, Response, and Recovery*, National Academies Press, 2007.
- [10] 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, <https://doi.org/10.1111/j.1539-6924.2012.01942.x>.
- [11] N. Mimura, K. Yasuhara, S. Kawagoe, H. Yokoki, S. Kazama, Damage from the great east Japan earthquake and Tsunami—a quick report, *Mitig. Adapt. Strategies Glob. Change* 16 (2011) 803–818, <https://doi.org/10.1007/s11027-011-9297-7>.
- [12] P. Slovic, B. Fischhoff, S. Lichtenstein, Rating the risks, *Environ. Sci. Policy Sustain. Dev.* 21 (3) (1979) 14–39, <https://doi.org/10.1080/00139157.1979.9933091>.
- [13] L. Sjöberg, B.E. Moen, T. Rundmo, Explaining Risk Perception. an Evaluation of the Psychometric Paradigm in Risk Perception Research (Working Paper No. 22), (Rotunde Publikasjoner Rotunde), 2004.
- [14] J. Barnett, G.M. Breakwell, Risk perception and experience: hazard personality profiles and individual differences, *Risk Anal.* 21 (1) (2001) 171–178, <https://doi.org/10.1111/0272-4332.211099>.
- [15] M. Bonaiuto, S. Alves, S. De Dominicis, I. Petruccielli, Place attachment and natural hazard risk: research review and agenda, *J. Environ. Psychol.* 48 (2016) 33–53, <https://doi.org/10.1016/j.jenvp.2016.07.007>.
- [16] W. Brun, Risk perception: main issues, approaches and findings, in: G. Wright, P. Ayton (Eds.), *Subjective Probability*, John Wiley & Sons, 1994, pp. 295–320.
- [17] S. De Dominicis, F. Fornara, U. Ganucci Cancellieri, C. Twigger-Ross, M. Bonaiuto, We are at risk, and so what? Place attachment, environmental risk perceptions and preventive coping behaviours, *J. Environ. Psychol.* 43 (2015) 66–78, <https://doi.org/10.1016/j.jenvp.2015.05.010>.
- [18] E. Gierlach, B.E. Belsher, L.E. Beutler, Cross-cultural differences in risk perceptions of disasters, *Risk Anal.* 30 (10) (2010) 1539–1549, <https://doi.org/10.1111/j.1539-6924.2010.01451.x>.
- [19] M. Siegrist, J. Árvai, Risk perception: reflections on 40 years of research, *Risk Anal.* 40 (S1) (2020) 2191–2206, <https://doi.org/10.1111/risa.13599>.
- [20] B. Xie, M.B. Brewer, B.K. Hayes, R.I. McDonald, B.R. Newell, Predicting climate change risk perception and willingness to act, *J. Environ. Psychol.* 65 (2019) 101331, <https://doi.org/10.1016/j.jenvp.2019.101331>.
- [21] P. Slovic, B. Fischhoff, S. Lichtenstein, Facts and fears: understanding perceived risk, in: R.C. Schwing, W.A. Albers (Eds.), *Societal Risk Assessment*, Springer US, 1980, pp. 181–216, https://doi.org/10.1007/978-1-4899-0445-4_9.
- [22] E.A. Rosa, The logical structure of the social amplification of risk framework (SARF): metatheoretical foundation and policy implications, in: N.K. Pidgeon, P. Slovic (Eds.), *The Social Amplification of Risk*, 2003, pp. 47–49.
- [23] R.E. Kasperson, O. Renn, P. Slovic, H.S. Brown, J. Emel, R. Goble, S. Ratick, The social amplification of risk: a conceptual framework, *Risk Anal.* 8 (2) (1988) 177–187, <https://doi.org/10.1111/j.1539-6924.1988.tb01168.x>.
- [24] T. Plapp, U. Werner, Understanding risk perception from natural hazards: examples from Germany, in: Dannenmann & Vulliet Amman (Ed.), *RISK 21 - Coping with Risks due to Natural Hazards in the 21st Century*, CRC Press, 2006, pp. 111–118.
- [25] R.W. Rogers, A protection motivation theory of fear appeals and attitude change, *J. Psychol.* 91 (1) (1975) 93–114, <https://doi.org/10.1080/00223980.1975.9915803>.
- [26] J.L. Demuth, R.E. Morss, J.K. Lazo, C. Trumbo, The effects of past hurricane experiences on evacuation intentions through risk perception and efficacy beliefs: a mediation analysis, *Weather Clim. Soc.* 8 (4) (2016) 327–344, <https://doi.org/10.1175/WCAS-D-15-0074.1>.
- [27] P. Slovic, E. Peters, M.L. Finucane, D.G. MacGregor, Affect, risk, and decision making, *Health Psychol.* 24 (4, Suppl) (2005) S35–S40, <https://doi.org/10.1037/0278-6133.24.4.S35>.
- [28] C. Keller, A. Bostrom, M. Kuttuschreuter, L. Savadori, A. Spence, M. White, Bringing appraisal theory to environmental risk perception: a review of conceptual approaches of the past 40 years and suggestions for future research, *J. Risk Res.* 15 (3) (2012) 237–256, <https://doi.org/10.1080/13669877.2011.634523>.
- [29] L. Watson, M.T. Spence, Causes and consequences of emotions on consumer behaviour: a review and integrative cognitive appraisal theory, *Eur. J. Market.* 41 (5/6) (2007) 487–511, <https://doi.org/10.1108/03090560710737570>.
- [30] H.D. Walpole, R.S. Wilson, Extending a broadly applicable measure of risk perception: the case for susceptibility, *J. Risk Res.* 24 (2) (2021) 135–147, <https://doi.org/10.1080/13669877.2020.1749874>.
- [31] P. Bubeck, W.J.W. Botzen, J.C. Aerts, A review of risk perception and other factors that influence flood mitigation behavior, *Risk Anal.: Int. J.* 32 (9) (2012) 1481–1495, <https://doi.org/10.1111/j.1539-6924.2011.01783.x>.
- [32] S. Schneiderbauer, P.F. Pisa, J.L. Delves, L. Pedoth, S. Rufat, M. Erschbamer, S. Granados-Chahin, Risk perception of climate change and natural hazards in global Mountain regions: a critical review, *Sci. Total Environ.* 784 (2021) 146957, <https://doi.org/10.1016/j.scitotenv.2021.146957>.
- [33] R.S. Wilson, A. Zwickle, H. Walpole, Developing a broadly applicable measure of risk perception, *Risk Anal.* 39 (4) (2019) 777–791, <https://doi.org/10.1111/risa.13207>.
- [34] L. Sjöberg, Consequences of perceived risk: demand for mitigation, *J. Risk Res.* 2 (2) (1999) 129–149, <https://doi.org/10.1080/136698799376899>.
- [35] L. Sjöberg, Consequences matter, 'risk' is marginal, *J. Risk Res.* 3 (3) (2000) 287–295, <https://doi.org/10.1080/13669870050043189>.
- [36] T. Okuhara, H. Okada, T. Kiuchi, Predictors of staying at home during the COVID-19 pandemic and social lockdown based on protection motivation theory: a cross-sectional study in Japan, *Healthcare* 8 (4) (2020) 475, <https://doi.org/10.3390/healthcare8040475>.
- [37] P. Slovic, B. Fischhoff, S. Lichtenstein, Rating the risks, in: Y.Y. Haimes (Ed.), *Risk/Benefit Analysis in Water Resources Planning and Management*, Springer, 1981, pp. 193–217, https://doi.org/10.1007/978-1-4899-2168-0_17.
- [38] G. Böhm, H.R. Pfister, Consequences, morality, and time in environmental risk evaluation, *J. Risk Res.* 8 (6) (2005) 461–479, <https://doi.org/10.1080/1366987050006413>.
- [39] 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, <https://doi.org/10.1111/j.1539-6924.2011.01647.x>.
- [40] M.K. Lindell, C.S. Prater, Household adoption of seismic hazard adjustments: a comparison of residents in two states, *Int. J. Mass Emergencies Disasters* 18 (2) (2000) 317–338, <https://doi.org/10.1177/028072700001800203>.
- [41] L. Sjöberg, Risk perception: experts and the public, *Eur. Psychol.* 3 (1) (1998) 1–12, <https://doi.org/10.1027/1016-9040.3.1.1>.
- [42] A. Boholm, Comparative studies of risk perception: a review of twenty years of research, *J. Risk Res.* 1 (2) (1998) 135–163, <https://doi.org/10.1080/136698798377231>.
- [43] 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, <https://doi.org/10.1007/s11069-018-3480-z>.
- [44] C. Solberg, T. Rossetto, H. Joffe, The social psychology of seismic hazard adjustment: re-evaluating the international literature, *Nat. Hazards Earth Syst. Sci.* 10 (8) (2010) 1663–1677, <https://doi.org/10.5194/nhess-10-1663-2010>.
- [45] M. Bonaiuto, S. Aricchio, La resilienza comunitaria: cornice concettuale e strumenti di misura, in: L. Caravaggi (Ed.), *Progetto SISMI-DTC Lazio Conoscenze E Innovazioni per la Ricostruzione E Il Miglioramento Sismico Dei Centri Storici Del Lazio*, Quodlibet, 2020, pp. 78–85.
- [46] J. Shi, V.H.M. Vischers, M. Siegrist, J. Árvai, Knowledge as a driver of public perceptions about climate change reassessed, *Nat. Clim. Change* 6 (2016) 759–762, <https://doi.org/10.1038/nclimate2997>.
- [47] S. van der Linden, The social-psychological determinants of climate change risk perceptions: towards a comprehensive model, *J. Environ. Psychol.* 41 (2015) 112–124, <https://doi.org/10.1016/j.jenvp.2014.11.012>.
- [48] A. Olofsson, S. Rashid, The white (male) effect and risk perception: can equality make a difference? *Risk Anal.* 31 (6) (2011) 1016–1032, <https://doi.org/10.1111/j.1539-6924.2010.01566.x>.

- [49] L. Sjöberg, Distal factors in risk perception, *J. Risk Res.* 6 (3) (2003) 187–211, <https://doi.org/10.1080/1366987032000088847>.
- [50] M. Douglas, A. Wildavsky, *Risk and Culture: an Essay on the Selection of Technological and Environmental Dangers*, Univ of California Press, 1982.
- [51] R.W. Rogers, S. Prentice-Dunn, Protection motivation theory, in: D. Gochman (Ed.), *Handbook of Health Behavior Research: Vol. 1. Determinants of Health Behavior: Personal and Social*, 1997, pp. 113–132. New York, NY Plenum.
- [52] D. Marikyan, S. Papagiannidis, Protection Motivation Theory: A review. TheoryHub Book: This handbook is based on the online theory resource: TheoryHub, S. Papagiannidis, 2003, pp. 78–93.
- [53] J.P. Mulilis, T.S. Duval, The PrE model of coping and tornado preparedness: moderating effects of responsibility, *J. Appl. Soc. Psychol.* 27 (19) (1997) 1750–1766, <https://doi.org/10.1111/j.1559-1816.1997.tb01623.x>.
- [54] H. Tan, Y. Hao, J. Yang, C. Tang, Meta-analyses of motivational factors of response to natural disaster, *J. Environ. Manag.* 351 (2024) 119723, <https://doi.org/10.1016/j.jenvman.2023.119723>.
- [55] G.H. Zamani, M.J. Gorgievski-Duijvesteijn, K. Zarafshani, Coping with drought: towards a multilevel understanding based on conservation of resources theory, *Hum. Ecol.* 34 (5) (2006) 677–692, <https://doi.org/10.1007/s10745-006-9034-0>.
- [56] T. Yu, H. Yang, X. Luo, Y. Jiang, X. Wu, J. Gao, Scientometric analysis of disaster risk perception: 2000–2020, *Int. J. Environ. Res. Publ. Health* 18 (24) (2021) 13003, <https://doi.org/10.3390/ijerph182413003>.
- [57] B. Fischhoff, P. Slovic, S. Lichtenstein, S. Read, B. Combs, How safe is safe enough? A psychometric study of attitudes towards technological risks and benefits, *Policy Sci.* 9 (2) (1978) 127–152, <https://doi.org/10.1007/BF00143739>.
- [58] P. Slovic, B. Fischhoff, S. Lichtenstein, Behavioral decision theory perspectives on risk and safety, *Acta Psychol.* 56 (1–3) (1984) 183–203, [https://doi.org/10.1016/0001-6918\(84\)90018-0](https://doi.org/10.1016/0001-6918(84)90018-0).
- [59] M.J. Page, D. Moher, P.M. Bossuyt, I. Boutron, T.C. Hoffmann, C.D. Mulrow, L. Shamseer, J.M. Tetzlaff, E.A. Akl, S.E. Brennan, R. Chou, J. Glanville, J. M. Grimshaw, A. Hróbjartsson, M.M. Lalu, T. Li, E.W. Loder, E. Mayo-Wilson, S. McDonald, J.E. McKenzie, PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews, *BMJ* n160 (2021), <https://doi.org/10.1136/bmj.n160>.
- [60] D. Moher, A. Liberati, J. Tetzlaff, D.G. Altman, Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement, *Int. J. Surg.* 8 (5) (2010) 336–341, <https://doi.org/10.1016/j.ijsu.2010.02.007>.
- [61] United Nations, Causes and effects of climate change. <https://www.un.org/en/climatechange/science/causes-effects-climate-change>, 2023.
- [62] The EndNote Team, *Endnote*. Clarivate, 2013. <https://myendnoteweb.com>.
- [63] A.M. Aloe, Inaccuracy of regression results in replacing bivariate correlations, *Res. Synth. Methods* 6 (1) (2015) 21–27, <https://doi.org/10.1002/jrsm.1126>.
- [64] J.L. Mumpower, X. Liu, A. Vedlitz, Predictors of the perceived risk of climate change and preferred resource levels for climate change management programs, *J. Risk Res.* 19 (6) (2016) 798–809, <https://doi.org/10.1080/13669877.2015.1043567>.
- [65] M.J. Hornsey, E.A. Harris, P.G. Bain, K.S. Fielding, Meta-analyses of the determinants and outcomes of belief in climate change, *Nat. Clim. Change* 6 (6) (2016) 622–626, <https://doi.org/10.1038/nclimate2943>.
- [66] M. Assink, C.J. Wibbelink, Fitting three-level meta-analytic models in R: a step-by-step tutorial, *The Quantitative Methods for Psychology* 12 (3) (2016) 154–174, <https://doi.org/10.20982/tqmp.12.3.p154>.
- [67] M.T. Rupinski, W.P. Dunlap, Approximating Pearson product-moment correlations from Kendall's Tau and Spearman's rho, *Educ. Psychol. Meas.* 56 (3) (1996) 419–429, <https://doi.org/10.1177/0013164496056003004>.
- [68] R.A. Peterson, S.P. Brown, On the use of beta coefficients in meta-analysis, *J. Appl. Psychol.* 90 (1) (2005) 175–181, <https://doi.org/10.1037/0021-9010.90.1.175>.
- [69] J. Sánchez-Meca, F. Marín-Martínez, S. Chacón-Moscó, Effect-size indices for dichotomized outcomes in meta-analysis, *Psychol. Methods* 8 (4) (2003) 448–467, <https://doi.org/10.1037/1082-989X.8.4.448>.
- [70] M. Borenstein, L.V. Hedges, J.P.T. Higgins, H.R. Rothstein, *Introduction to Meta-Analysis*, John Wiley & Sons, 2021.
- [71] W. Viechtbauer, Conducting meta-analyses in R with the metafor package, *J. Stat. Software* 36 (3) (2010), <https://doi.org/10.18637/jss.v036.i03>.
- [72] R.E. Dunlap, K.D. Van Lier, A.G. Mertig, R.E. Jones, New trends in measuring environmental attitudes: measuring endorsement of the new ecological paradigm: a revised NEP scale, *J. Soc. Issues* 56 (3) (2000) 425–442, <https://doi.org/10.1111/0022-4537.00176>.
- [73] J.P.A. Ioannidis, N.A. Patsopoulos, E. Evangelou, Uncertainty in heterogeneity estimates in meta-analyses, *BMJ* 335 (7626) (2007) 914–916, <https://doi.org/10.1136/bmj.39343.408449.80>.
- [74] W. Van den Noortgate, J.A. López-López, F. Marín-Martínez, J. Sánchez-Meca, Meta-analysis of multiple outcomes: a multilevel approach, *Behav. Res. Methods* 47 (4) (2015) 1274–1294, <https://doi.org/10.3758/s13428-014-0527-2>.
- [75] E. Kontopoulis, D. Reeves, Performance of statistical methods for meta-analysis when true study effects are non-normally distributed: a simulation study, *Stat. Methods Med. Res.* 21 (2012) 409–426, <https://doi.org/10.1177/0962280210392008>.
- [76] A. Lovakov, E.R. Agadullina, Empirically derived guidelines for effect size interpretation in social psychology, *Eur. J. Soc. Psychol.* 51 (3) (2021) 485–504, <https://doi.org/10.1002/ejsp.2752>.
- [77] H.R. Rothstein, A.J. Sutton, M. Borenstein, Publication bias in meta-analysis, in: *Publication Bias in Meta-Analysis*, Wiley, 2005, pp. 1–7, <https://doi.org/10.1002/0470870168.ch1>.
- [78] N.A. Card, *Applied Meta-Analysis for Social Science Research*, Guilford Publications, 2015.
- [79] B. Egger, Y. Klafegger, A. Theis, W. Salzburger, A sensory bias has triggered the evolution of egg-spots in cichlid fishes, *PLoS One* 6 (10) (2011) e25601, <https://doi.org/10.1371/journal.pone.0025601>.
- [80] M. Egger, G.D. Smith, M. Schneider, C. Minder, Bias in meta-analysis detected by a simple, graphical test, *BMJ* 315 (7109) (1997) 629–634, <https://doi.org/10.1136/bmj.315.7109.629>.
- [81] M.W. Lipsey, Those confounded moderators in meta-analysis: good, bad, and ugly, *Ann. Am. Acad. Polit. Soc. Sci.* 587 (1) (2003) 69–81, <https://doi.org/10.1177/0002716202250791>.
- [82] R. Fu, G. Gartlehner, M. Grant, T. Shamliyan, A. Sedrakyan, T.J. Wilt, L. Griffith, M. Oremus, P. Raina, A. Ismail, P. Santaguida, J. Lau, T.A. Trikalinos, Conducting quantitative synthesis when comparing medical interventions: AHRQ and the effective health care program, *J. Clin. Epidemiol.* 64 (11) (2011) 1187–1197, <https://doi.org/10.1016/j.jclinepi.2010.08.010>.
- [83] R. Stojanov, B. Duží, T. Daněk, D. Němec, D. Procházka, Adaptation to the impacts of climate extremes in central Europe: a case study in a rural area in the Czech Republic, *Sustainability* 7 (9) (2015) 12758–12786, <https://doi.org/10.3390/su70912758>.
- [84] Y. Kryvasheyev, H. Chen, N. Obradovich, E. Moro, P. Van Hentenryck, J. Fowler, M. Cebrian, Rapid assessment of disaster damage using social media activity, *Sci. Adv.* 2 (3) (2016) e1500779, <https://doi.org/10.1126/sciadv.1500779>.
- [85] N.C. Bronfman, P.C. Cisternas, E. López-Vázquez, L.A. Cifuentes, Trust and risk perception of natural hazards: implications for risk preparedness in Chile, *Nat. Hazards* 81 (2016) 307–327, <https://doi.org/10.1007/s11069-015-2080-4>.
- [86] S. De Dominicis, W.D. Crano, U. Ganucci Cancellieri, B. Mosco, M. Bonnes, Z. Hohman, M. Bonaiuto, Vested interest and environmental risk communication: improving willingness to cope with impending disasters, *J. Appl. Soc. Psychol.* 44 (2014) 364–374, <https://doi.org/10.1111/jasp.12229>.
- [87] S. De Dominicis, U. Ganucci Cancellieri, W.D. Crano, A. Stancu, M. Bonaiuto, Experiencing, caring, coping: vested interest mediates the effect of past experience on coping behaviors in environmental risk contexts, *J. Appl. Soc. Psychol.* 51 (2021) 286–304, <https://doi.org/10.1111/jasp.12735>.
- [88] A. Panno, G. Carrus, F. Maricchiolo, L. Mannetti, Cognitive reappraisal and pro-environmental behavior: the role of global climate change perception, *Eur. J. Soc. Psychol.* 45 (7) (2015) 858–867, <https://doi.org/10.1002/ejsp.2162>.
- [89] L.R. Larson, S.B. Castleberry, G.T. Green, Effects of an environmental education program on the environmental orientations of children from different gender, age, and ethnic groups, *J. Park Recreat. Adm.* 28 (3) (2010).
- [90] K. Kaniasty, Social support, interpersonal, and community dynamics following disasters caused by natural hazards, *Curr. Opin. Psychol.* 32 (2020) 105–109, <https://doi.org/10.1016/j.copsyc.2019.07.026>.

- [91] A. Spence, W. Poortinga, N. Pidgeon, The psychological distance of climate change, *Risk Anal.: Int. J.* 32 (6) (2012) 957–972, <https://doi.org/10.1111/j.1539-6924.2011.01695.x>.
- [92] B.B. Johnson, P. Slovic, Presenting uncertainty in health risk assessment: initial studies of its effects on risk perception and trust, *Risk Anal.* 15 (4) (1995) 485–494, <https://doi.org/10.1111/j.1539-6924.1995.tb00341.x>.
- [93] O. De Zwart, I.K. Veldhuijzen, G. Elam, A.R. Aro, T. Abraham, G.D. Bishop, J. Brug, Perceived threat, risk perception, and efficacy beliefs related to SARS and other (emerging) infectious diseases: results of an international survey, *Int. J. Behav. Med.* 16 (2009) 30–40, <https://doi.org/10.1007/s12529-008-9008-2>.
- [94] R.C. Stedman, Toward a social psychology of place: predicting behavior from place-based cognitions, attitude, and identity, *Environ. Behav.* 34 (5) (2002) 561–581, <https://doi.org/10.1177/0013916502034005001>.
- [95] M. Bonaiuto, S. De Dominicis, F. Fornara, U. Ganucci Cancellieri, B. Mosco, Flood risk: the role of neighbourhood attachment, in: G. Zenz, R. Hornich (Eds.), *Proceedings of the International Symposium UFRIM. Urban Flood Risk Management - Approaches to Enhance Resilience of Communities*, Graz: Verlag der Technischen Universität Graz, 2011, pp. 547–558. ISBN 978-3-85125-173-9.
- [96] S. Ariccio, I. Petruccielli, U. Ganucci Cancellieri, C. Quintana, P. Villagra, M. Bonaiuto, Loving, leaving, living: evacuation site place attachment predicts natural hazard coping behavior, *J. Environ. Psychol.* 70 (2020) 101431, <https://doi.org/10.1016/j.jenvp.2020.101431>.
- [97] A. Stancu, S. Ariccio, S. De Dominicis, U. Ganucci Cancellieri, I. Petruccielli, C. Ilin, M. Bonaiuto, The better the bond, the better we cope. The effects of place attachment intensity and place attachment styles on the link between perception of risk and emotional and behavioral coping, *Int. J. Disaster Risk Reduct.* 51 (2020) 101771, <https://doi.org/10.1016/j.ijdr.2020.101771>.
- [98] A. Stancu, S. Ariccio, S. De Dominicis, U. Ganucci Cancellieri, I. Petruccielli, A. Theodorou, C. Ilin, M. Bonaiuto, Place attachment styles predict adaptive and maladaptive conducts under flood risk: evidence via cognitive and affective coping mediation, *J. Community Appl. Soc. Psychol.* 35 (2025) e70083, <https://doi.org/10.1002/casp.70083>.
- [99] P.E. Gustafson, Gender differences in risk perception: theoretical and methodological perspectives, *Risk Anal.* 18 (6) (1998) 805–811, <https://doi.org/10.1111/j.1539-6924.1998.tb01123.x>.
- [100] R.B. Cialdini, R.R. Reno, C.A. Kallgren, A focus theory of normative conduct: recycling the concept of norms to reduce littering in public places, *Journal of Personality and Social Psychology* 58 (6) (1990) 1015. <https://psycnet.apa.org/doi/10.1037/0022-3514.58.6.1015>.
- [101] R.B. Cialdini, C.A. Kallgren, R.R. Reno, A focus theory of normative conduct: a theoretical refinement and reevaluation of the role of norms in human behavior, *Adv. Exp. Soc. Psychol.* 24 (1991) 201–234, [https://doi.org/10.1016/S0065-2601\(08\)60330-5](https://doi.org/10.1016/S0065-2601(08)60330-5).
- [102] J. Thøgersen, Norms for environmentally responsible behaviour: an extended taxonomy, *J. Environ. Psychol.* 26 (4) (2006) 247–261, <https://doi.org/10.1016/j.jenvp.2006.09.004>.
- [103] P. Slovic, B. Fischhoff, S. Lichtenstein, The psychometric study of risk perception, in: V.T. Covelio, J. Menkes, J. Mumpower (Eds.), *Risk Evaluation and Management, Contemporary Issues in Risk Analysis*, vol. 1, Springer, 1986, pp. 3–24, https://doi.org/10.1007/978-1-4613-2103-3_1.
- [104] A. Milani, F. Dessi, M. Bonaiuto, A meta-analysis on the drivers and barriers to the social acceptance of renewable and sustainable energy technologies, *Energy Res. Social Sci.* 114 (2024) 103624, <https://doi.org/10.1016/j.erss.2024.103624>.
- [105] J.M. Rohrer, Thinking clearly about correlations and causation: graphical causal models for observational data, *Advances in methods and practices in psychological science* 1 (1) (2018) 27–42, <https://doi.org/10.1177/2515245917745629>.
- [106] E. Maidl, D.N. Bresch, M. Buchecker, Social integration matters: factors influencing natural hazard risk preparedness—a survey of Swiss households, *Nat. Hazards* 105 (2) (2021) 1861–1890, <https://doi.org/10.1007/s11069-020-04381-2>.
- [107] J.J. O'Sullivan, R.A. Bradford, M. Bonaiuto, S. De Dominicis, P. Rotko, J. Aaltonen, K. Waylen, S.J. Langan, Enhancing flood resilience through improved risk communications, *Nat. Hazards Earth Syst. Sci.* 12 (2012) 2271–2282, <https://doi.org/10.5194/nhess-12-2271-2012>.
- [108] C. Gilbert, K. Lachlan, The climate change risk perception model in the United States: a replication study, *J. Environ. Psychol.* 86 (2023) 101969, <https://doi.org/10.1016/j.jenvp.2023.101969>.