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Threat, coping and flood prevention – A meta-analysis

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A B S T R A C T

In order to understand flood preventive intentions and behaviors in individuals, the research literature of the last decades has turned to the Protection Motivation Theory (PMT; Rogers, 1975, 1983) as a prominent framework. Yet a meta-analytical synthesis of these research results is still missing. The present meta-analysis combines correlation and regression coefficients reported from 35 single studies using 47 independent samples ($N = 35{,}419$). Data analysis shows that threat appraisal ($r+ = 0.23$) and coping appraisal ($r+ = 0.30$) are both significantly associated with flood preventive intentions/behaviors. Meta-analytical structural equation modeling (MASEM) indicates that flood-related emotions and trust in public institutions qualify as additional predictors, whereas past flood experiences qualify only as an indirect predictor. Overall, the extended PMT model explains 15% of variance in flood preventive intentions/behaviors. In relation to the effect size (ES) variability, meta-analytical ANOVAs confirm a moderating impact of the dependent variable (intention vs. behavior), and of the date of publication (before or after 2012). Implications for future research are discussed.

1. Introduction

Flooding inflicts severe costs on societies, especially on the rural inhabitants of developing countries where flood protection measures are mostly inadequate. Experts estimate that more than 700 million people worldwide (10% of the world's population) are currently prone to disastrous flooding. Between 1970 and 2010, this number increased by 114% (UNISDR, 2011). One example of the life-threatening potential of flooding was Typhoon Haiyan, killing more than 3900 people when it hit the Philippines in 2013. Flood-related economic losses are expected to rise drastically in the next years. For Europe, annual losses because of continental flooding are estimated to increase from currently €4.9 billion to €23.5 billion by 2050 (Jongman et al., 2014).

Estimates like these have fueled discussions concerning the effectiveness of traditional flood protection strategies and their focus on structural protection measures (dikes and levees): Although levees generally do reduce the risk of flooding, they also increase the potential flood damage when their defense fails (e.g. Lane, Landström, & Whatmore, 2011). The limitations of solely structural flood defense strategies (Johnson, Penning-Rowsell, & Tapsell, 2007) have initiated a shift towards more integrated flood risk management strategies (Bubeck, Kreibich et al., 2012; European Commission, 2007; Kreibich, Bubeck, Van Vliet, & De Moel, 2015). Attributing greater responsibility to private households has been an important consequence of this development: While earlier strategies mainly held public authorities responsible for flood risk management, integrated strategies demand private households to play a more active role in protecting their life and property from flooding.

Calls for active participation of private households are based on studies that have demonstrated the effectiveness of flood preventive measures adopted by individual households. Such measures, including flood-adapted building, mobile flood barriers, or the securement of sources of contamination, can reduce the damages of household property up to 80 percent (Holub & Fuchs, 2008; Kreibich et al., 2015; Olfert & Schanze, 2008). Consequentially, private engagement in flood protection has become an important component of current risk management strategies (Bubeck, Botzen, & Aerts, 2012; Bubeck, Kreibich, et al., 2012). In many European countries policy directives now dictate that those endangered by flooding are obliged to undertake appropriate measures to reduce flood-related damages.

However, past survey studies indicate that even in flood prone areas most citizens are not ready to accept this responsibility (e.g. Krasovskaia, 2005; Kreibich et al., 2011; Terpstra, 2010). For example, the vast majority of interviewed participants in the

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Netherlands (85%) stated that they had hardly ever thought about their risk of flooding; 73% still considered the government to be primarily responsible for flood protection. Similarly, only 33% of surveyed households in Germany were aware that their building was located in a flood prone area. Finally, in a survey of 4000 residents in flood prone areas in Germany, the Netherlands, Norway, Sweden, and the UK, more than 80 percent of the participants reported that they had not taken any precautionary measures and only a minority of the households judged such measures effective. Gaining a better understanding of the factors that motivate individuals to improve their flood preparedness has become an important scientific task.

Initially, most of the research in this field focused on the relationship between flood risk perceptions and (the uptake of) private flood preventive behaviors (e.g., Plapp & Werner, 2006). Yet empirical results only revealed weak or insignificant correlations between risk perceptions and the adoption of preventive measures, thus hinting at a more complex picture (cf. Bubeck, Botzen, et al., 2012; for a review). Grothmann and Reusswig (2006) demonstrated how a well-established psychological theory - Rogers's (1983) Protection Motivation Theory (PMT) - could be used to increase our knowledge of the processes mediating the impact of flood risk perceptions on flood preventive intentions/behaviors. Following their research, a number of studies have investigated the psychological determinants of private flood protective action.

The goal of the paper at hand is to provide a meta-analytical synthesis of studies applying concepts derived from the PMT for flood-related research. While previous work has provided narrative reviews (Bubeck, Botzen, et al., 2012; Kellens, Terpstra, & De Maeyer, 2013), a meta-analytical (i.e., quantitative) synthesis is - to the best of our knowledge - still missing. The present research aims at filling this gap. Our second, more method-related goal relates to the possible use of standardized regression coefficients as a substitute for not reported bivariate correlations. In the literature, this method is discussed as a strategy to increase the number of studies available for estimating the "true" population's effect sizes. The following section introduces the PMT and its applications. We continue by stating our hypotheses and the methods applied, especially the use of regression coefficients as correlation substitutes. Presentation of the results of bivariate random-effects meta-analyses and of meta-analytical structural equation models (MASEM) follow. In the last section, we discuss implications for future research.

2. Protection motivation theory

Initially, the Protection Motivation Theory (PMT) was proposed as a framework for understanding the impact of fear appeals on (favorable) behavioral choices (Rogers, 1975; 1983). Like other social-cognitive theories (e.g., theory of planned behavior), PMT is an expectancy-value theory. It states that people will jointly evaluate the likelihood of being exposed to a certain threat, the severity of that threat, and their ability to cope it (Fig. 1).

PMT focuses on four central constructs: threat vulnerability (i.e., appraised likelihood of threat exposure), threat severity (i.e., perceived consequences of threat exposure), response efficacy (i.e., perceived effectiveness of the protective behavior), and self-efficacy (i.e., capability to perform the protective behavior). Threat vulnerability and severity are grouped under the term "threat appraisal", while response and self-efficacy are collectively called "coping appraisal" (Rogers, 1983). When the level of threat appraisal is low, individuals - usually - will not be motivated to adopt the protective behavior. If threat appraisal is moderate to high (and possibly complemented by fear of threat), adoption of the protective behavior is contingent with the results of the coping

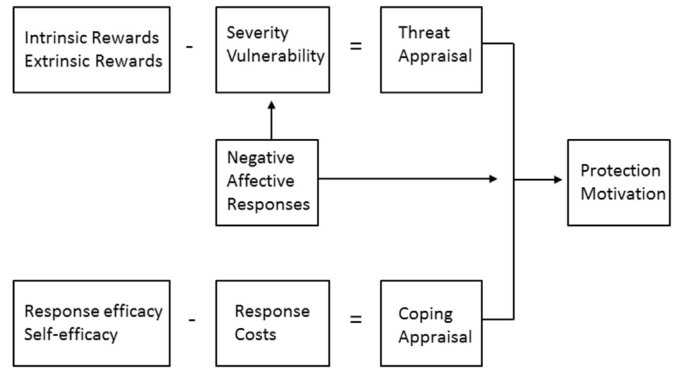

Fig. 1. The protection motivation theory (Rogers, 1975, 1983).

appraisal process. Again, moderate to high levels of coping appraisal will increase a person's motivation to engage in the behavior to reduce the threat (i.e., protection motivation), while low levels of coping ability increase the likelihood of maladaptive coping behavior (e.g., fatalism, denial).

With regard to health-related behaviors, two meta-analyzes have quantified the results of previous PMT studies. The first meta-analysis (Floyd, Prentice-Dunn, & Rogers, 2000) was based on 65 studies that targeted more than 20 health-related behaviors (e.g., AIDS prevention, drug consumption, cancer prevention, exercise/diet behaviors). As expected, they found positive pooled correlations between intention/concurrent behavior and threat appraisal ($r+ = 0.26$) as well as coping appraisal ($r+ = 0.20$). The second meta-analysis (27 studies; Milne, Sheeran, & Orbell, 2000) revealed a slightly different pattern, indicating that intentions/behaviors were more strongly correlated with coping appraisal than with threat appraisal. They also found a positive pooled correlation between intentions/behaviors and fear ($r+ = 0.20$ - 0.26). In sum, these results have supported the proposed PMT model. Yet, the correlations between coping or threat appraisal and intentions/behaviors were low to moderate. This may hint at other processes, apart from those proposed by the PMT that may play a role in motivating individuals in taking up protective behavior.

3. The present research

The aim of our meta-analysis is to provide a quantitative synthesis of the empirical research on PMT variables associated with individual flood preventive behavior. In line with the PMT we assume that both threat and coping appraisal underlie a person's intention to engage in flood preventive behaviors or her/his actual performance of such behaviors. However, reviewing the empirical evidence for this assumption is important because for one of the PMT components - threat appraisal - previous narrative reviews of flood related studies have pointed at a statistically insignificant or only weak relation between "flood risk perceptions and the adoption of private flood mitigation measures" (Bubeck, Botzen, et al., 2012, p. 1482). The second PMT component - coping appraisal - was discussed in the literature review by Bubeck, Botzen, et al. (2012) and Bubeck, Kreibich, et al. (2012), drawing the conclusion that "overall, these findings support the argument that coping appraisal is an important determinant for private flood mitigation behavior" (p. 1493). However, both conclusions are based on a narrative review of 16 papers published between 2002 and 2011. Subsequent research has cited Bubeck et al.'s work as a central argument for their claim that threat appraisal only plays a minor role in understanding a person's motivation for flood protection. However, the limited empirical basis of the review might not justify such a strong claim. Furthermore, studies that adhered to the PMT more strongly did indeed find the expected relation between threat appraisal and protective intentions/behaviors (Grothmann & Reusswig, 2006; Zaalberg, Midden, Meijnders, & McCally, 2009). From this we derive the following hypotheses:

H1a. As postulated by the PMT, coping appraisal is positively associated with flood preventive intentions/behaviors.

H1b. As postulated by the PMT, threat appraisal is positively associated with flood preventive intentions/behaviors.

To be fair, Bubeck, Botzen, et al. (2012) and Bubeck, Kreibich, et al. (2012) provide a detailed conceptual account of the threat appraisal component. Drawing upon the work of Weinstein (1998) they intensively discuss a methodological problem possibly responsible for the weak threat appraisal-behavior relation: Almost all published papers used cross-sectional designs, studying the relationship between threat appraisal and concurrent precautionary behaviors. This neglects a possible feedback from an already-adopted flood mitigation measure with regard to the respondent's threat appraisal. One way to avoid this methodological problem is to ask respondents which intentions they might have in performing flood mitigation measures in the future. With regard to future behavior, the relationship between risk perceptions and the intention to mitigate should not be distorted by previous mitigation behavior. If Bubeck, Botzen, et al. (2012) and Bubeck, Kreibich, et al. (2012) were right the results of our meta-analysis should support the following hypothesis:

H2. The correlation between threat appraisal and behavioral intention should be significantly stronger than the correlation between threat appraisal and concurrent behavior.

Next to the cognitive PMT constructs, many researchers consider "hot" affective processes (e.g., anxiety, fear or worries resulting from past flood experiences) to be independent additional predictors of flood preventive intentions/behaviors (e.g., Tapsell, Penning-Rowsell, Tunstall, & Wilson, 2002). Theoretically, this assumption is justified by the "risk-*as*-feelings" hypothesis, proposing that affective processes exert a direct influence on intentions/behaviors (Loewenstein, Weber, Hsee, & Welch, 2001), which leads to the following hypothesis:

H3a. Flood-related negative emotions, like anxiety, fear or worries, have a significant positive association with flood preventive intentions/behaviors.

However, Loewenstein et al. (2001) do not only expect affective processes to exert a direct influence on intentions/behaviors, they also claim that emotions mediate, at least in part, the impact of cognitive appraisal processes on behavioral outcomes. Somewhat similarly, Slovic, Finucane, Peters, and MacGregor (2004) assume that affective processes do not influence behaviors directly but only indirectly via their impact on probability judgments, as suggested by the "affect-*as*-information" hypothesis (cf. Clore, Gasper, & Garvin, 2001). This means that when people evaluate the likelihood of a risky event occurring, they rely on prior affective experiences, current feelings and images associated with that event. The next hypothesis summarizes these assumptions:

H3b. Flood-related negative emotions have a positive indirect effect on flood preventive intentions/behaviors via their impact on the cognitive threat appraisal process.

Grothmann and Reusswig (2006) also discussed the role of trust in public flood protection for private flood preventive behaviors. They found that people with high levels of trust in public institutions were less likely to take up flood mitigation measures (Botzen, Aerts, & van den Bergh, 2009). According to Babcicky and Seebauer (2016), trust was associated with lower risk perception levels, which, in turn, undermined respondents' intentions to engage in private flood mitigation. From this research we derive two further hypotheses:

H4a. Trust in public flood protection measures is negatively associated with private flood preventive intentions/behaviors.

H4b. Trust in public flood protection measures has a negative indirect effect on private flood preventive intentions/behaviors through its direct negative impact on threat appraisal and flood-related negative emotions.

Previous research has also discussed the possible impact of past flooding experiences on flood-related appraisals and protective intentions/behaviors (Begg, Ueberham, Masson, & Kuhlicke, 2016; Boamah et al., 2015; Bubeck, Botzen, et al., 2012; Bubeck, Kreibich, et al., 2012). For example, Weinstein (1989) suggested that personal experience informs risk perception: People who have recently experienced flooding may judge the probability and severity of a flood to be greater than people without such experiences. Recent flood experiences were also positively associated with the intensity of flood-related anxiety, fear or worries. This research provides the background for our last two hypotheses:

H5a. Past flood experiences are positively associated with flood preventive intentions/behaviors.

H5b. Past flood experiences have an indirect positive effect on flood preventive intentions/behaviors through their direct impact on threat appraisal, flood-related emotions, and trust in public flood protection. We expect past flood experiences to be positively associated with threat appraisal and flood-related emotions but negatively correlated with trust in public flood protection.

4. Material and methods

4.1. Search strategy

Our systematic search finished in October 2016. We used two search strategies to ensure a comprehensive literature review: First, four databases were searched for keywords, titles, and abstracts (Web of Science, SCOPUS, PsycINFO, Google Scholar). Different keyword combinations (e.g., ["flooding" AND "Protection Motivation Theory"]) yielded 770 records. Second, forward and backward searches were performed by searching the reference lists of key papers and review articles (e.g., Bubeck, Botzen, et al., 2012; Bubeck, Kreibich, et al., 2012). Abstract and full text screenings - if necessary - of all identified records were completed. Papers were included in the next step if they (1) reported at least one quantitative relationship between two of the research variables of our hypotheses, and (2) were published in English or German.[1] In total, 221 eligible papers remained.

4.2. Extraction of data

Data extraction was guided by a protocol based on precise construct definitions (cf. Appendix A) derived from Grothmann and Reusswig (2006), Rogers (1983), as well as Bubeck, Botzen, et al. (2012) and Bubeck, Kreibich, et al. (2012). The first author screened the remaining 221 papers for empirical associations between the following constructs: flood preventive intentions/

[1] Language barriers prevented us from including other publications in the analysis.

behaviors, threat appraisal, coping appraisal, flood-related negative emotions, trust in public flood protection, and past flood experience. We only extracted the data if at least two constructs fit our definitions. Additional bibliometric information (e.g., journal name, peer review, year of publication, country of study, authors' training and institution) and methodological information (data collection technique, type of sample, reliability of measurement instruments) were also collected. Second and third authors repeated the screening and extraction process for seventy studies independently to ensure sufficient interrater reliability. Disagreements were resolved by consensus among the coders.

Data extraction focused on information concerning bivariate associations such as Pearson's *r*, Spearman's *r*, Kendalls *Tau*, *Phi* etc. We also extracted all other statistics (χ^2-test with $df = 1$, *t-test* with *df*, and *odds ratio*) that could be converted into the *r* effect-size metric system (e.g. Lipsey & Wilson, 2000). However, a substantial number of suitable studies (in our case 30% of the 47 independent samples identified) did not report bivariate associations among the variables but only the results of multiple linear or logistic regression analyzes. Due to their model dependency, standardized regression coefficients (*ß*) usually are not included as a measurement for effect-sizes in meta-analyses (e.g., Hunter & Schmidt, 1990). Yet omitting these papers would have entailed a substantial loss of empirical data that is directly relevant to the PMT test within the domain of flooding. Past research on meta-analytical methods (e.g., Peterson & Brown, 2005) agrees that there are at least three potential threats to possible inferences when estimating population effect sizes and variances only on the basis of the available bivariate effect sizes: (1) Omitting relevant effect sizes fails to make use of available information and ignores studies that may be essential to an accurate understanding of effect sizes and the conditions that generate them. (2) Omitting relevant effect sizes increases sampling errors, which decrease the precision of meta-analytic estimates of population parameters. (3) Omission decreases the extent to which the set of effect sizes included in a meta-analysis properly represents the universe of designs and contexts from which the population parameters would emerge.

Consequently, recent research on multivariate meta-analytic methods (e.g., Becker & Wu, 2007; Borenstein, Hedges, Higgins, & Rothstein, 2009; Stanley & Jarrell, 2005) has focused on understanding the conditions under which *ß* values can be accepted as an effect size metric to estimate population effect sizes. Peterson and Brown (2005) made a substantial contribution to this literature by examining the relationship between *ß* and correlation coefficients (*r*). Within a sample of more than 1500 studies in the social sciences, they found that the correlation between *ß* and *r* values was extremely high ($r = 0.84$). The number of independent variables in a regression equation was also not related to the divergence between *ß* and *r*. In other words, *ß* corresponds to *r* quite well regardless of the number of covariates in the regression equation. Consequently, using different covariates across studies does not seem to systematically affect the estimate of *ß*. Peterson and Brown (2005) also compared the utility of several equations that conveyed the relationship between *ß* and *r*; their analyzes showed that the straightforward equation $ß = r$ performed just as well as any other equation, particularly when betas were fairly close to zero. They concluded that *ß* values can directly substitute *r* values in a quantitative meta-analysis. Against this methodological background, we decided to extract standardized regression coefficients (*ß*) and treat them as correlation coefficients in our meta-analysis. We also extracted logistic regression coefficients, converted them into odds and then into *r*.[2]

[2] Additionally, we sent an e-mail to the authors of eligible studies that did not report bivariate correlations and asked them to provide the correlation matrices of their analyzes. Despite a follow-up e-mail two weeks later only one author sent us the requested data.

4.3. Meta-analytical data synthesis

In the context of field studies conducted in different settings and environments, using a random effects-model for calculation of the weighted average ES has been recommended (Borenstein et al., 2009). The random (vs. fixed) effects-model assumes the existence of a distribution of true ES (instead of a single true effect μ), reflecting the impact of different conditions and contexts across different studies. A weighted average ES, therefore, does not reflect a single effect μ but it rather equates the (population) mean of the true effects instead. When using the random effects-model, we need to consider two levels of sampling and two sources of error. Firstly, the true effect sizes θ are distributed around μ with a variance τ^2, which reflects the actual distribution of the true effects around their mean. Secondly, the observed effect T for any given θ will be distributed around that value of θ with a variance σ^2, which depends primarily on that study's sample size. Therefore, in assigning weights to estimate μ, we need to deal with both sources of sampling error – within studies (ε) as well as between studies (ζ).

In the present meta-analysis, we used correlations as an ES metric, based on the Hedges and Olkin (1985) method. We converted the raw correlations into a standard normal metric by applying Fisher's *r* -to-*z* transformation. We then calculated an initial pooled mean correlation in which each primary correlation is weighted by the inverse of its variance. Studies with smaller samples (i.e., greater variance) were thus given less weight. Following this step we calculated the *Q*-test statistic of homogeneity for each pooled correlation. Lastly, the pooled *z*-transformed correlations were re-converted into the *r* metric. To test our hypotheses, we also used the meta-analytically pooled correlation matrix of the constructs as input into a so-called meta-analytic structural equation model (MASEM, Bamberg & Möser, 2007; Becker, 2000; Viswesvaran & Ones, 1995). This method allows to specify and to test multivariate path models on the basis of the meta-analytically pooled correlation matrices.

5. Results

5.1. Results of the data extraction process

We initially identified a total of 221 possibly eligible papers. Closer inspection of these papers revealed that 35 out of 221 studies (including 47 independent samples) reported empirical data with regard to the association of at least two constructs targeted in our meta-analysis. The 47 independent samples comprised a total of $N = 35{,}419$ participants (harmonic mean sample size $N = 298$). Due to the fact that many studies used the same sample to calculate correlations for different types of flood protective intentions/behaviors, the 35 selected studies reported a total of 90 single correlations/correlation matrices. To avoid double counting, we averaged multiple correlations based on the same sample before including the data into the analysis. The pooled mean general ES of our meta-analysis were thus obtained from a maximum of 47 independent samples.

5.2. Description of the studies

A summary of the information extracted from all 35 studies can be found in Appendix B. The majority of the studies were published in 21 different English-speaking (exception: 2 German-speaking paper), peer-reviewed journals (exception: 8 dissertations, reports, and book chapters). We also included "grey" research reports and book chapters that - after reading - were rated acceptable in quality. Within the widespread literature, only two journals ("Natural Hazards" seven papers, "Risk Analysis" four papers) published more than two of the identified papers. All studies were based on surveys conducted in 15 different countries (23 in European countries, mainly Germany, The Netherlands, and France; 4 in the USA, and 8 in Asian countries: China, Malaysia, Japan, India, Vietnam, and Cambodia). The earliest paper included in our meta-analysis was published in 2003 the latest four studies were published in 2016. Since 2011, there has been a significant raise in the number of published papers: 70% of all identified papers were published within the last six years. On the one hand this indicates that flood researchers are increasingly interested in applying and testing psychological models like the PMT, on the other hand it emphasizes the need to reappraise the conclusions drawn by earlier narrative reviews on the predictive power of the PMT constructs.

5.3. The meta-analytically pooled total effect size matrix

We have specified nine hypotheses (see above) that address the associations among the following six constructs: (1) flood preventive behavioral intentions/behaviors, (2) threat appraisal, (3) coping appraisal, (4) flood-related negative emotions, (5) past flooding experiences, and (6) trust in public flood protection. Table 1 presents the total sample sizes and the total number of independent estimates (*r* and *ß* values), which were included for calculating the bivariate associations between these six constructs reported in Table 2.

As can be seen in Table 1, 39 studies (total $N = 25{,}231$; 26 studies reporting *r* values, and 13 studies reporting *ß* values) reported empirical data on the association between flood preventive intentions/behaviors and threat appraisal and 27 studies (total $N = 16{,}177$; 17 studies reporting *r* values, and 10 studies reporting *ß* values) reported empirical data on the association between flood preventive intentions/behaviors and coping appraisal. These study numbers provided a solid empirical basis to test hypotheses H1a and H1b. Fig. 2 presents the results of funnel plots checking for these studies the presence of publication bias.

For both associations our subjective impression does not support the presence of a grave asymmetrical distribution of reported effect sizes. However, Table 1 also shows that we have considerably less information concerning the intercorrelations among the five predictors of flood preventive intentions/behaviors. Especially trust in public flood protection (H4a & H4b) has only been assessed by few studies. Table 2 presents the matrix of the *z*-to-*r* reversely transferred pooled bivariate correlations between the six constructs (random-effects model) calculated with all *r* and *ß* effect sizes.

Table 1
Total sample size (upper row) and number of independent correlations (lower row) extracted for each construct.

Construct	1	2	3	4	5	6
1. Intention/behavior	–					
2. Threat appraisal	25,231 (39)	–				
3. Flood-related emotions	17,570 (16)	5521 (10)	–			
4. Coping appraisal	16,177 (27)	5871 (11)	2023 (4)	–		
5. Past flood experiences	12,665 (24)	5472 (16)	3165 (10)	3208 (10)	–	
6. Trust in public flood protection	9996 (12)	5120 (15)	7991 (13)	3208 (4)	245 (2)	–

Table 2
Pooled total effect size matrix (correlation and betas, random-effects model, reversed transformation from Fisher's Z).

Construct	1	2	3	4	5	6
1. Intention/behavior	–					
2. Threat appraisal	0.23[a]	–				
3. Flood-related emotions	0.17[a]	0.31[b]	–			
4. Coping appraisal	0.30[a]	0.10[c]	0.02	–		
5. Past flood experiences	0.13[a]	0.15[a]	0.11[b]	0.12[a]	–	
6. Trust in public flood protection	0.03	−0.15[b]	−0.30[a]	−0.02	−0.11	–

Note. Pooled correlations are significant at [a] $p < 0.001$, [b] $p < 0.01$, [c] $p < 0.05$.

The pooled bivariate correlations between flood preventive intentions/behaviors and threat appraisal ($r+ = 0.23$) and coping appraisal ($r+ = 0.30$) respectively are statistically significant, albeit of moderate size. Furthermore, the *95% CIs* for the two pooled correlations presented in Table 3 overlap with the *95% CI* reported by Floyd et al. (2000) in their meta-analysis for these two pooled correlations (*95% CI* pooled intentions/behaviors – threat appraisal = 0.25 - 0.37; pooled intentions/behaviors – coping appraisal = 0.13 - 0.27). For the coping – intention/behavior association the *Fail-safe N* is 8.650, for the threat – intention/behavior association the *Fail-safe N* is 2.758. The results, thus, confirm H1a and H1b postulating that coping appraisal and threat appraisal are both significantly associated with individual flood preventive intentions/behaviors. The meta-analytical results also support H3a as well as our assumptions concerning the negative emotion-threat appraisal relation (H3b): The pooled correlations between flood-related negative emotions and flood preventive intentions/behaviors ($r+ = 0.17$) and threat appraisal ($r+ = 0.31$) respectively are positive and significant. Furthermore, our findings do not provide evidence for H4a: The pooled correlation of trust with intentions/behaviors does not reach significance ($r+ = 0.03$). Yet, threat appraisal ($r+ = -0.15$) and flood-related negative emotions ($r+ = -0.30$) are both negatively associated with trust, hinting at a possible indirect effect of trust on intentions/behaviors (H4b). Due to the small number of studies, all results related to trust should be interpreted with caution. As expected (H5a and H5b), past flood experiences show positive (but low) associations with intentions/behaviors ($r+ = 0.13$), threat appraisal ($r+ = 0.15$), and flood-related emotions ($r+ = 0.11$), but is negatively correlated with trust in public flood protection ($r+ = -0.11$).

5.4. Sensitivity test of r vs. ß based effect sizes

Due to the debate concerning the validity and reliability of *ß* values as population effect size estimates, a sensitivity analysis is highly recommendable. For this purpose, Table 4 and Table 5 present the meta-analytically pooled effect size estimates for the extracted *r* and *ß* effect sizes separately. Because they are based on a sufficient number of studies, we will focus on the two pooled effect size estimates "threat appraisal – intention/behavior" and "coping appraisal – intention/behavior" in our sensitivity analysis. A meta-analytical ANOVA version (e.g., Borenstein et al., 2009; Lipsey & Wilson, 2000) indicates that both pooled effect size estimates are significantly different from each other: The *r*-based effect size of the pooled threat appraisal – intention/behavior effect size estimate is $r+ = 0.27$, while the *ß*-based effect size of the pooled threat appraisal – intention/behavior effect size estimate is only $r+ = 0.14$; $Q_{df=1} = 340.82$, $p < 0.001$. The *r*-based effect size of the pooled coping appraisal – intention/behavior effect size estimate is $r+ = 0.36$, while the *ß*-based effect size of the pooled coping appraisal – intention/behavior effect size estimate again is only $r+ = 0.14$. This difference is also statistically significant

Threat Appraisal and intention/behavior – funnel plot

Coping Appraisal and intention/behavior – funnel plot

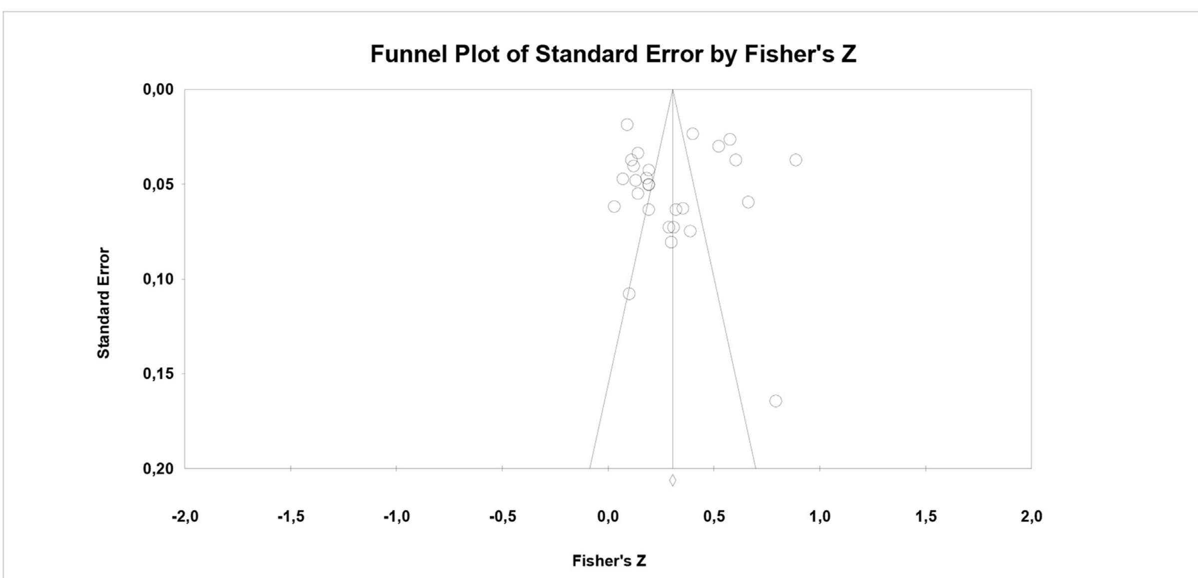

Fig. 2. Funnel plots.

Table 3
95% confidence intervals of the pooled total effect sizes (cf. Table 2).

Construct	1	2	3	4	5
1. Intention/behavior	–				
2. Threat appraisal	0.16–0.31	–			
3. Flood-related emotions	0.13–0.21	0.09–0.56	–		
4. Coping appraisal	0.21–0.39	0.10–0.20	−0.04–0.07	–	
5. Past flood experiences	0.08–0.19	0.10–0.20	0.04–0.17	0.05–0.19	–
6. Trust in public flood protection	−0.03–0.09	−0.26–−0.04	−0.36–−0.26	−0.06–0.03	−0.24–0.01

Table 4
Pooled effect sizes based on correlations only (number of studies in brackets).

Construct	1	2	3	4	5
1. Intention/behavior	–				
2. Threat appraisal	0.27[a] (26)	–			
3. Flood-related emotions	0.17[a] (14)	0.37[b] (7)	–		
4. Coping appraisal	0.36[a] (17)	0.17[a] (10)	0.02 (4)	–	
5. Past flood experiences	0.12[a] (18)	0.16[a] (15)	0.11[b] (10)	0.12[a] (10)	–
6. Trust in public flood protection	−0.02 (7)	−0.05 (10)	−0.30[a] (9)	−0.04 (3)	−0.11 (2)

Note. Pooled effect sizes are significant at [a] $p < 0.001$, [b] $p < 0.01$.

Table 5
Pooled effect sizes based on betas only (number of studies in brackets).

Construct	1	2	3	4	5
1. Intention/behavior	–				
2. Threat appraisal	0.14[a] (13)	–			
3. Flood-related emotions	0.21[b] (2)	0.22[a] (3)	–		
4. Coping appraisal	0.14[a] (10)	-0.06 (1)	−(0)	–	
5. Past flood experiences	0.13 (6)	0.05 (1)	−(0)	−(0)	–
6. Trust in public flood protection	0.11[a] (5)	−0.35[a] (5)	−0.34[a] (4)	0.08 (1)	−(0)

Note. Pooled correlations are significant at [a] $p < 0.001$, [b] $p < 0.01$.

($Q_{df=1} = 412.59, p < 0.001$). Because ß values are partial coefficients that reflect the influence of all predictor variables in a multiple regression model, it is not surprising that the ß-based pooled effect size estimate is significantly lower than the *r*-based pooled effect size. It is more surprising, however, that we also found the opposite pattern (cf. Tables 4 and 5): For example, the pooled threat appraisal – trust effect size estimate based on *r* values is significantly smaller than the pooled threat appraisal – trust effect size estimate based on ß values (*r* values+ = −0.05 vs. ß values = −0.35, $Q_{df=1} = 66.81$, $p < 0.001$). Table 5 also reveals a disadvantage typically associated with studies reporting only results from multiple regressions: Because they focus on the prediction of one dependent variable, information concerning the intercorrelation of the predictors is mostly left unreported. The empty cells in Table 5 reflect this disadvantage of regression based studies.

5.5. Meta-analytical test of additional moderator effects

Next to checking the impact of choosing *r* or ß on the meta-analytically pooled effect size estimates, we used meta-analytical ANOVAs to find the effects of two other possible moderators of the predictor – intentions/behaviors effect sizes: (1) type of dependent variable (intention vs. behavior), and (2) date of publication (before or after 2012).

(1) Aim of this ANOVA analysis: test H2, i.e., Bubeck, Botzen, et al. (2012) and Bubeck, Kreibich, et al. (2012) postulate that threat appraisal is more strongly correlated with flood preventive intentions than with flood preventive behaviors. However, our results do not confirm H2 (cf. Table 6). On the contrary, the correlation was significantly stronger between threat appraisal and behavior (r+ = 0.33) than threat appraisal and intentions (r+ = 0.26).

(2) When considering papers published before 2012, ANOVA results reveal a stronger correlation between intentions/behaviors and coping appraisal (*r*+ = 0.47) than threat appraisal (*r*+ = 0.25). This supports the conclusions drawn by Bubeck, Botzen, et al. (2012) and Bubeck, Kreibich, et al. (2012). However, we found the opposite pattern in papers published after 2012: Intentions/behaviors were more strongly correlated with threat appraisal (*r*+ = 0.33) than with coping appraisal (*r*+ = 0.20). Furthermore, papers published after 2012 report a slightly stronger pooled intentions/behaviors – past flood experience correlation (*r*+ = 0.14) than the papers published before 2012 (*r*+ = 0.06) (cf. Table 7).

Table 6
Results of the meta-analytical ANOVA: Pooled correlations of intention vs. concurrent behavior (number of studies in brackets).

Construct	Behavior	Intention	Meta-ANOVA, df = 1
Threat appraisal	0.33 (17)	0.26 (21)	Q = 33.94[a]
Flood-related emotions	0.17 (5)	0.19 (10)	Q = 2.11
Coping appraisal	0.22 (13)	0.33 (13)	Q = 45.98[a]
Past flood experiences	0.16 (14)	0.03 (8)	Q = 41.45[a]
Trust in public flood protection	0.01 (2)	0.06 (10)	Q = 1.19

Note. [a] $p < 0.001$.

5.6. MASEM results

We have focused on meta-analytically pooled bivariate correlations thus far. Although this is an important first step, merely examining synthesized correlations can only provide a limited (i.e., bivariate) test of the model structure proposed by the PMT. In order to obtain a multivariate test of our hypotheses, we conducted meta-analytic structural equation modeling (so-called MASEM) based on the pooled correlation matrix as seen in Table 2.[3] Fig. 3 presents the results of three path models: the basic PMT model (Model 1), the adapted PMT model proposed by Grothmann and Reusswig (Model 2), and an extended PMT model based on our hypotheses (Model 3).

Model 1 includes threat appraisal, coping appraisal, and flood-related negative emotions as direct determinants of flood preventive intentions/behaviors. All postulated paths are statistically significant (cf. Fig. 3: Model 1). The model accounts for 13% of the variance in the intentions/behaviors variable and the fit indices exhibit an acceptable model fit (Hu & Bentler, 1999). In Model 2 we

[3] A MASEM often poses a methodological problem: Most of the synthesized studies do not report all of the elements included in the matrix. Consequently, the elements of the pooled correlation matrix are based on different sample sizes (cf. Table 1). Yet to calculate a MASEM, data on the common sample size is needed to estimate p-values and model fit. Previous research has suggested using the harmonic mean for this purpose which in the present MASEM amounts to N = 298.

Table 7
Results of the meta-analytical ANOVA: Date of publication as moderator (number of studies in brackets).

Correlated constructs	Before 2012	After 2011	*Meta*-ANOVA df = 1
Threat appraisal – intent/behav	0.25 (19)	0.33 (20)	Q = 32.64[a]
Flood emotions– intent/behav	0.17 (9)	0.18 (7)	Q = 0.50
Coping appraisal– intent/behav	0.47 (12)	0.20 (15)	Q = 300.59[a]
Past flood – intent/behav	0.06 (12)	0.14 (12)	Q = 16.50[a]
Trust – intent/behave	−0.04 (6)	0.09 (6)	Q = 29.97[a]

Note. [a] $p < 0.001$.

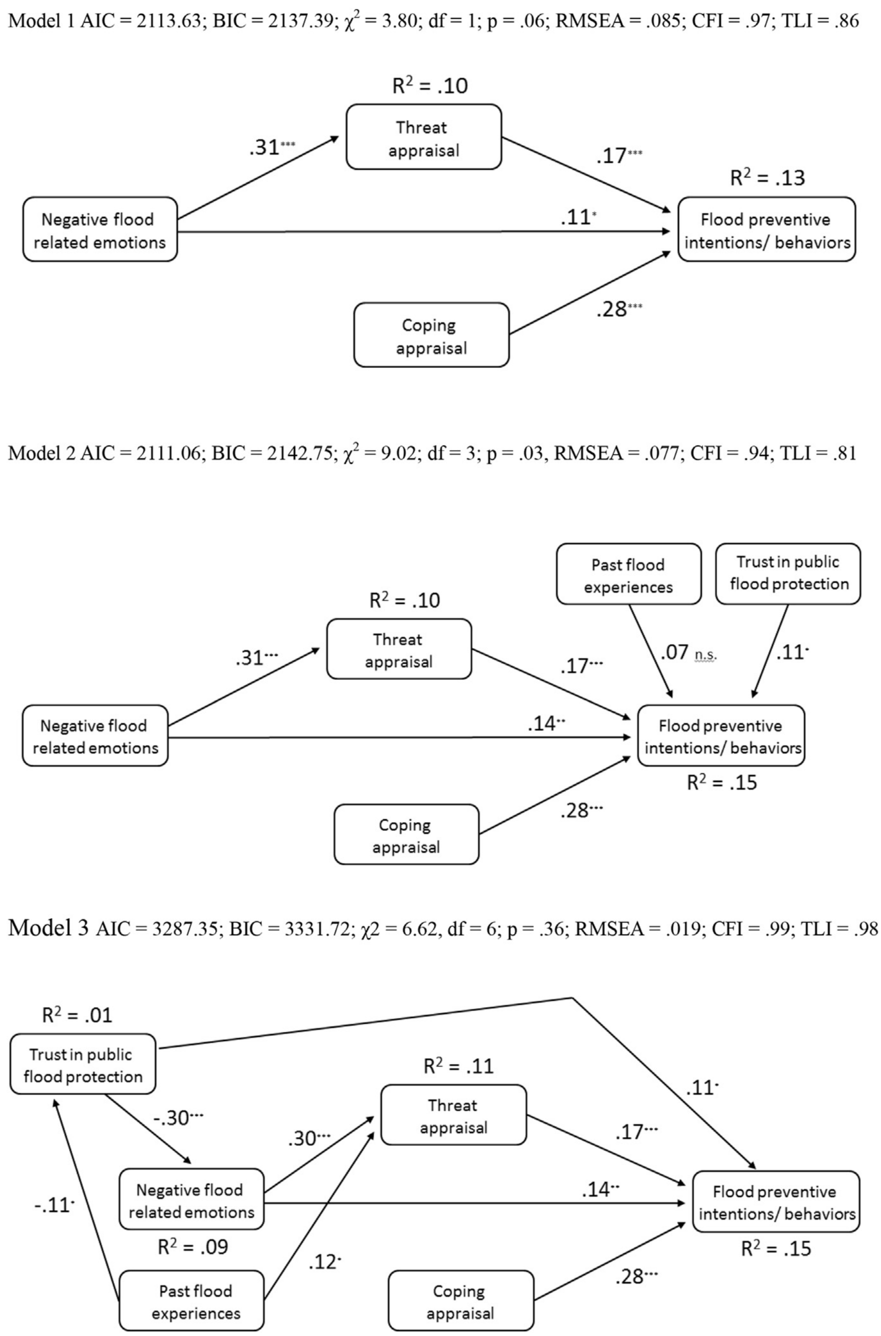

Fig. 3. Results of the MASEM analyses. Note. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

have added past flood experiences and trust in public flood protection as direct predictors of flood preventive intentions/behaviors (cf. Fig. 3: Model 2). However, only the trust – intentions/behaviors path is significant. By including these two additional predictors the model's total predictive power has increased slightly from 13% (Model 1) to 15% (Model 2). The model fit is still acceptable. Model 3 contains all paths derived from our hypotheses (cf. Fig. 3: Model 3). Apart from the trust → threat appraisal path and the past flood experience → emotions path all postulated paths are significant. The model accounts for 15% of the variance in the intentions/behaviors variable. Fit indices indicate good model fit (*$\chi 2 = 6.62$, $df = 6$; $p = .36$, RMSEA $= .019$; CFI $= .99$; TLI $= .98$*). Results indicate that threat and coping appraisals, flood-related negative emotions, and trust in public institutions are all direct predictors of flood preventive intentions/behaviors, thus supporting H1a, H1b, H3a, and H5a. The model also confirms H3b (i.e., indirect effect of negative emotions through threat appraisal) and partly confirms H4b (i.e., indirect effect of trust through emotions), and H5b (i.e., indirect effect of past flood experience through threat appraisal). Interestingly, the direct path from institutional trust to intentions/behaviors ($ß = 0.11$) is significant, albeit the positive path coefficient provides no evidence for H4. Furthermore, the significant trust → intentions/behaviors path seems to be somewhat inconsistent with the insignificant bivariate correlation between the two variables ($r+ = 0.03$). Model 3 provides a possible explanation for this discrepancy: The insignificant bivariate correlation might simply be the result of the competition between direct and indirect effects of trust on intentions/behaviors.

6. Discussion and conclusion

The aim of the present meta-analysis is to provide a quantitative synthesis of the research conducted (since the 1990s) on the significance of PMT constructs in predicting flood preventive intentions/behaviors. We are - to the best of our knowledge - the first to investigate predictors of individual flood protection behaviors by means of a meta-analysis.

6.1. Using ß values to substitute for unreported r values

After our meta-analytical search and data extraction stages we were confronted with the fact that about one third of the relevant studies did not report bivariate but only multivariate results on the relationship between flood preventive intentions/behaviors and the PMT predictors. Encouraged by the growing body of methodological literature, we decided to use both the available r values as well as $ß$ values to calculate integrated random effects pooled correlations. At the current state of debate, however, we strongly recommend the use of sensitivity analyzes in order to report and compare the results of random effects pooled correlations calculated for the available r and $ß$ values separately. In our case, the results of the sensitivity analysis are mixed: With regard to the two central pooled effect size estimates “threat appraisal – intention/behavior” and “coping appraisal – intention/behavior” the results are in line with our expectations. Using partial $ß$-coefficients produces significantly lower, yet still statistically significant pooled correlations. On the other hand, the pooled threat appraisal – trust effect size estimate based on r values is significantly smaller than the estimate based on $ß$ values. One reason for this unexpected finding may be the relatively low number of studies that make up the basis for these results. A proper strategy in dealing with studies reporting only multivariate $ß$ values may be their inclusion into analysis while also making sure to conduct a sensitivity analysis and to interpret the integrated pooled ES as lower bound of the “true” population ES.

6.2. Predictive power of the PMT variables

The PMT considers threat appraisal and coping appraisal to be central factors in the uptake of protective behaviors, yet an influential recent review has concluded that only coping (but not threat) appraisal predicts flood preventive intentions/behaviors (Bubeck, Botzen, et al., 2012; Bubeck, Kreibich, et al., 2012). As a result, newer publications (after 2012) have tended to ascribe less importance to the theoretical and empirical investigation of threat appraisal processes. Our results demonstrate that this conclusion lacks empirical support and is, therefore, premature at best: Our meta-analytical synthesis of the total number of effect sizes reported in 39, respectively 27 independent studies shows that the pooled bivariate correlations between flood preventive intentions/behaviors and coping appraisal ($r+ = 0.30$) and threat appraisal ($r+ = 0.23$) are both statistically significant and similarly strong (supporting H1a and H1b). The multivariate MASEM results confirm these findings: Also after controlling for the effects of additional predictors, the associations between both flood preventive intentions/behaviors and threat appraisal as well as coping appraisal remain statistically significant. Furthermore, as predicted by the “risk-*as*-feelings” hypothesis, the MASEM analyses reveal that emotions also have an impact on threat appraisal and flood preventive intentions/behaviors: Flood-related negative emotions directly and indirectly (through their positive association with cognitive threat appraisal) affected flood preventive intentions/behaviors (supporting H3a & H3b). This is in line with the results of PMT meta-analyses in different behavior domains (e.g., health behaviors; Milne et al., 2000) and with psychological research that highlights the role of affect in decision making (i.e., “risk as feelings”; Kobbeltvedt & Wollf, 2009; Loewenstein et al., 2001).

6.3. Past flood experiences and trust in public flood protection

Bubeck, Botzen, et al. (2012) and Bubeck, Kreibich, et al. (2012) consider past flood experience as a suitable variable to extend the basic PMT model (and possibly to complement threat appraisal). However, our meta-analytical results only partly support this view. As expected, past flood experience was negatively associated with trust in public flood protection and positively associated with threat appraisal (partial support for H5b). Yet both correlations are small. The results of the MASEM analysis confirm that past flood experience is not a significant predictor for flood preventive intentions/behaviors (no support for H5a). Even more astonishingly, our findings did not reveal a significant association between past flood experience and negative flood-related emotions (Grothmann & Reusswig, 2006). This either hints at a methodological issue in the measurement of past flood experience (i.e., current measures do not capture the psychologically relevant aspects). Alternatively, flood-related emotions may reflect the impact of other psychological processes that are not an immediate result of dealing with previous flood events. In sum, our results suggest that past flood experience is more of an indirect predictor of private flood protection measures and its effect is mediated by other psychological processes. Future research needs to focus on providing a theory-driven, detailed understanding of how past flood experience, especially experiences of multiple flood events (Walker-Springett, Butler, & Adger, 2017), influences flood-related emotions, threat appraisal and non-protective coping styles (e.g., fatalism, wishful thinking).

Our meta-analysis also provides tentative evidence for the ambivalent effects of trust in public flood protection on private flood preventive behaviors. On the one hand, trust was negatively associated with anticipated negative flood-related emotions (but not threat appraisal), which, ultimately, led to less preventive intentions/behaviors (partially supporting H4b). On the other hand, our results - somewhat surprisingly - exhibit a direct positive association between trust and preventive intentions/behavior (no support for H4a). Although unexpected, this may reflect the positive impact of public efforts to fight flooding by asserting personal responsibility to engage in *complementary* individual flood protection behaviors (Babcicky & Seebauer, 2016). Our suggestion is to interpret these results with caution as they are based on a relatively small number of studies and they represent a rather heterogeneous set of trust measures.

6.4. Moderator effects

The extended PMT model explains about 15 percent of variance in reported flood preventive intentions/behaviors. There are (at least) two reasons for the considerable share of unexplained variance: Firstly, the model does not account for a number of potentially important factors of flood preventive intentions/behaviors, including resource-related factors (e.g., household income), individual differences in coping styles (e.g., display of non-protective coping styles), protection-related attitudes, and social norms (see below). Secondly, the limited predictive power of the PMT model may stem from factors that are biased towards the correlations between the five predictors and flood preventive intentions/behaviors.

Results of our moderator analyses lend some support to this latter assumption. We found significant interaction effects for the two additional moderator types: dependent variable and date of publication. However, the moderator analyses did not always yield a consistent pattern of results. For example, meta-analytic ANOVAs revealed that three out of five predictors were associated differently with both private flood preventive variables (behavioral intention vs. concurrent behavior). Yet, our results contradict Bubeck et al.'s expectations as well as our H2: For two out of the three predictors, the pooled correlations concerning concurrent behavior were higher than their correlations on intentions. Regarding the date of publication (before vs. after 2012), we detected a consistent impact change of threat and coping appraisals on private flood protection over time. While the effect of coping (vs. threat) appraisal on preventive action was stronger in earlier studies, threat appraisal has been more predictive of preventive action in recent studies. At this point, we can only speculate as to the reasons why. In sum, our analyses provide evidence that part of the observed ES variability can be attributed to method, time, and theory related to the moderators. At the same time, future meta-analyses will need to test the robustness of these findings and to investigate additional moderators, including type of behavior (e.g., information seeking vs. structural measures) and study design (correlational, experimental, longitudinal design).

6.5. Future research & limitations

Against the backdrop of our research results we derive the following recommendations for future research on flood preventive intentions/behaviors:

6.5.1. Conceptual integration and development

Our results show a relatively moderate predictive power of the extended PMT model for flood preventive intentions/behaviors. One way to increase the share of explained variance is a theory-driven (i.e., parsimonious) inclusion of additional variables into the model. Valuable insights may come from the systematic comparison between the PMT and alternative social-cognitive theories/models, such as the Protective Action Decision Model (PADM, Lindell & Perry, 2012), the Theory of Planned Behavior (TPB; Ajzen, 1991), the Risk Information Seeking and Processing Model (RISP, Griffin, Dunwoody, & Neuwirth, 1999), or the Motivation-Intention-Volition Model (MIV, Martens, Garrelts, Grunenberg, & Lange, 2009). For example, the PMT does not include the social normative factor (i.e., social norms) incorporated in the TPB and the RISP model. Yet the decision to adopt specific protective behaviors (or not) might be influenced by a number of factors, for instance the expectations of (significant) other persons (Saeri, Ogilvie, Macchia, Smith, & Louis, 2014). Similarly, integrating research on different processing modes of risk-related information (RISP) could improve our understanding of the relation between risk perception and the uptake of protective behaviors (Yang, Aloe, & Feeley, 2014). Finally, the PMT somewhat neglects volitional processes known to mediate the intention-behavior relationship (Martens et al., 2009). Applying insights gained by these alternative models may, thus, help to improve the predictive power of the current PMT model for flood preventive behaviors.

We also suggest to take a “fresh” look at the interplay between some of the constructs included in the current PMT model as well as the psychological processes mediating the effects of more distal predictors of preventive intentions/behaviors (cf. Bonaiuto, Alves, De Dominicis, & Petruccelli, 2016; for this purpose). For instance, future research may investigate how cognitive and affective processes interact during the threat appraisal process. Past work has demonstrated that cognitive and affective processes both affect threat appraisal (i.e., “risk as feelings” and “risk as analysis”) but little is known about their interplay in the formation of risk-related behavioral intentions (Slovic & Peters, 2006). Similarly, future studies could test possible moderator effects of past flood experience with regard to the relation between threat appraisal and protection behaviors. For example, multiple experiences of flooding may simultaneously increase the strength of associations between emotions or threat appraisal and flood preventive intentions/behaviors (Walker-Springett et al., 2017). Trust in public flood protection also lends itself to be a candidate for future research efforts. Previous work provides tentative evidence that trust might affect flood preventive intentions/behaviors in different but competing ways: Trust negatively influenced risk perception which, in turn, led to lower intentions/behaviors. Yet trust (as form of social capital) may also increase the perceived personal efficacy to fight flooding, thus positively contributing to the uptake of private protection behaviors (Babcicky & Seebauer, 2016). Future meta-analyses are to investigate this possibly ambivalent character of trust, based on a - hopefully - larger body of studies available. A more precise and standardized measurement of trust (e.g., trust in public institutions vs. trust in other community members) would support these future research efforts considerably.

6.5.2. Data availability

Because of the aforementioned problems associated with the high proportion of relevant studies reporting not enough information for calculating bivariate associations, we kindly ask and urge (future) authors and members of editorial boards to pay more attention to the sufficient provision of statistical data in the submitted manuscripts. From a methodological perspective, it would also be desirable to apply Structural Equation Modeling (SEM) more frequently (longitudinal study design preferred). SEM allows for the estimation of latent variables and complex mediating mechanisms. Although previous reviews have highlighted the need for experimental and longitudinal studies to allow causal inferences, the number of such studies is still small (Kellens et al., 2013). Consequently, most of the studies included in our meta-analysis employed a correlational design. Because correlations allow no causal inferences, the validity of such data for testing causal hypotheses (in our case derived from the PMT) is limited. Milne et al.

(2000) have provided an overview of experimental designs/paradigms used for testing causal hypotheses derived from the PMT. We are convinced that these designs offer a valuable point of reference to improve research on the social and psychological mechanisms underlying the formation of flood preventive intentions/behaviors.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jenvp.2017.08.001.

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