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# The near-miss effect in flood risk estimation: A survey-based approach to model private mitigation intentions into agent-based models☆

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ABSTRACT

Behavioral reactions to natural hazards, including floods, and mitigation intentions are strongly predicted by risk perception. Among the different psychological processes forging individuals' risk-estimation, the present work focuses on the near-miss effect, the human tendency to underestimate the risks when a previous negative outcome is avoided by chance. Study 1 ($N = 241$) investigates the near-miss effect among residents of both flood-prone and safe areas, showing that participants exposed to near-miss scenarios perceive a lower level of risk and damages regardless of their past experience with the hazard, and thus are less prone to adopt protective measures. Based on the data collected in Study 1, Study 2 develops a series of agent-based models to simulate the effect of experiencing near-miss events on a neighborhood in a flood-prone area, where inhabitants have to decide whether to purchase insurance against flood-related damage. The agent-based models integrating the psychological parameters reveals that the underestimation of the likelihood of flooding due to the near-miss effect is likely to increase the negative economic consequences of disasters suffered by the population. The work shows, at a population level, how psychological factors and human responses to risk might tailor the economic consequences of flood-related events. Implications for risk management and communication are discussed.

## 1. Introduction

In 2022, the Intergovernmental Panel on Climate Change [1] warned once again that if the global warming level exceeds 1.5 °C in the next few years, governments and local authorities worldwide will soon be forced to deal with increasingly more severe and widespread impacts of natural hazards, including flooding from heavy precipitation and sea-level rise in coastal areas. Under these conditions, improving the accuracy of flood risk estimation models will be crucial to help optimize public policies and the allocation of resources to manage the consequences of flooding events [2,3].

Although in anthropic environments disaster risk derives from the interplay of environmental and social drivers (e.g., incorrect decisions, wrong policies, and lack of situational awareness among authorities and the general public), in most cases risk models are built on hydrogeological, engineering, and economic parameters, with little consideration of exposure, vulnerability and impacts of

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human systems [1,4]. In the plethora of socio-cultural, political, and physical processes conditioning disasters occurrence, individuals' perception and cognitive processes are likely to affect human responses to risk[1]. Given the centrality of human impact in flood risk, engineering and hydrological models of flood risk estimation could greatly benefit from psychologically grounded accounts concerning human risk perception and precautionary behavior, which are in continuous interplay with hydrological processes (see socio-hydrology approach, [5,6]).

Research has already shown a clear relation between risk and various social, cognitive and affective factors, such as perceived risk, perceived response efficacy, self-efficacy, feelings of worry, decision makers' competences, and preparedness towards several types of hazard, including flood events [7–10]. The present research sought to extend this strand of studies by investigating the interaction effect of near-misses (i.e., the avoidance of hazard's negative outcomes by chance [11]); and prior experience with flood events on risk perception and consequent intentions to adopt mitigation strategies. Moreover, based on survey data collected from population living in actual flood-prone areas, we developed a series of computational models (Agent Based Models, ABMs) trying to account for the near-miss effect on adoption of private mitigation measures (i.e., insurance purchase) at a population level. Through such models, it was possible to investigate the potential impact of psychological processes (i.e., near-miss effect) and behavioral intentions on flood economic damages in a hypothetical neighborhood.

## 2. Flood risk perception, past experience, and near-miss events

Prior research on human responses in hydrological processes and flood events [12] has emphasized the importance of the strategies adopted by private stakeholders, households, local communities, and institutions (e.g., using flood protection devices, adapting buildings, purchasing insurance) to mitigate flood-related damages and decrease risk [13,14]. Thus, identifying the critical antecedents of willingness to adopt mitigation strategies is becoming more and more relevant for risk management and communication.

Among these antecedents, risk perception - a probabilistic evaluation and intuitive judgment of the occurrence of an adverse event made by laypeople [15–17] - plays a critical role. For decades, cognitive psychology highlighted a series of biases and heuristics that intervene on people's causal inference, inductive reasoning, awareness, and subjective probability assessment (e.g., [18]), thus being potentially critical in risk perception and interpretation. As highlighted by seminal works (e.g., [19–22]), although risk perception is inherently subjective and often deviates from actual risk [16], this process is fundamental to investigating human behavioral reactions to hazards, including natural and flood hazards [7,23]. Indeed, a high level of risk perception is related to an increased perceived probability of personally experiencing the adverse impacts of the event, which in turn would make people more prone to adopt mitigation measures and hazard adjustments [14,24–30].

### *2.1. Past experience and risk perception*

The literature highlighted various psychological variables and processes likely to influence people's risk perception, ranging from cognitive and affective biases to social influence [7–9]. Among these, it is well established that past experiences with dangerous scenarios are likely to shape and increase perception of risk for similar future situations. Studies documented positive associations between flood experience, perception of floods risk [31–33], and consequent undertaking of flood mitigation actions [34–36]. After experiencing damage from extreme weather events (e.g., floods or tornados), people tend to be more concerned about environmental risks [37–39] and more willing to undertake risk-reducing measures (e.g., [40–42]). Furthermore, the literature on psychological distance [43] showed that risk perception markedly increases when disastrous events are represented as psychologically close (in terms of space or time), can be readily imagined, or have been newly experienced by affected population (e.g., [44]).

### *2.2. Near-miss and risk perception*

Although the positive relationship between past experience and risk perception has been extensively supported by empirical evidence, at a closer look, the link between the two phenomena appears to be more complex. Indeed, experiencing disasters does not always lead to higher perceived risk. Especially when the experienced hazard does not have severe adverse outcomes, the past experience might even decrease individuals' risk estimation [24,45–50].

Psychological accounts focusing on near-miss events [51–53] might explain such contradictory findings. Near-miss events include risky scenarios like natural hazards, terrorist attacks, or pandemics with a non-trivial probability of producing serious negative outcomes (economic damages, injuries and loss of lives) which, however, are ultimately avoided largely by chance. In the case of natural hazards, the complex dynamics of causal drivers results in large variability of outcome severity, spanning from extreme disasters to near-miss situations without negative impacts for exposed people. When a near-miss occurs, people tend to consider the danger as successfully avoided, underestimate similar hazardous situations and make riskier decisions, unduly feeling more resilient to possible negative consequences. This biased outcome of the evaluation process might be due to hindsight and outcome bias - the tendency to judge past decision or behavior based on its outcome [54,55] - that might hinder *downward counterfactual* thought where the outcome was worse than what happened [56,57]. In such a near-miss condition, the positive relations usually found in the literature between the experienced event, risk perception, and intentions to engage in protective behaviors disappear both in an experimental [11] and a naturalistic setting [58]. This phenomenon might explain the main findings of pioneering studies [59] that showed that the most sig-

[1] In the present work, among different variables and processes that can be broadly categorized as psychological, we mainly focus on cognition and perception. Cognitive psychology is the theoretical framework of the study. Thus, other psychological factors (for instance, psychological well-being, resilience, coping strategies) that are strongly related to experience with natural disasters and individual and communities' reactions to adverse events [99–101] were not considered.

nificant predictor of flood insurance purchase was whether the respondent living in a risk-prone area experienced damage during floods.

Overall, this strand of research suggests that past experience is not always positively related to risk prevention. However, to our knowledge, no prior study explicitly explored the interaction between the effects of past experience with hydrometeorological risks and of near-miss events. Thus, it is still unclear if the exposure to near-misses may overcome past experience effects, reducing risk perception - and the consequent willingness to adopt mitigation measures - among inhabitants of a flood-prone area holding significant personal experience with the negative consequences of flood events.

## 3. Integrating psychological processes into agent-based models

As discussed above, the accuracy of risk estimation relative to environmental hazards such as floods can be improved by accounting for the psychological processes driving human behavior in these situations. However, investigating the actual impact of such behaviors requires an analysis of the complex interactions typically found at a population level. To this end, a helpful tool are agent-based models (ABMs).

The ABMs are computational simulations in which various artificial agents - discrete entities situated in an artificial environment - are set up to interact over time with other agents within ad-hoc built environments [60]. Such models allow the investigation of how patterns observed at a global, systemic level can emerge from the repeated interactions of simple units [61]. In this way, it is possible to have a better intuition of population-scale dynamics that would be difficult to predict based on observing single individuals' behaviors.

A recent line of studies attempted to integrate psychological dimensions (e.g., risk perception; behavioral intentions; mitigation promptness) into engineering models of flood risk estimation. Additionally, to guarantee the resemblance between the simulated scenario and its real-world counterpart, many authors highlighted the importance of basing these computational simulations on empirical data drawn from psychological research, expert knowledge, surveys, and qualitative interviews of the local population [10,12,62–67].

To further increase the ecological validity of the models' predictions, and consequently the validity of the insights derived from these simulations, some works did strive to estimate psychological parameters based on ad-hoc empirical data. For example, [68] tested risk communication strategies deriving critical attributes from an on-field survey among flood-prone households [69], whereas [63] estimated parameters for a flood loss model by collecting both quantitative and qualitative survey data from a flood-prone area. Last, [70] modeled intentions to use social media for seeking help during hurricanes based on a survey of social media use. By extending this promising strand of research, it might be possible to improve the precision of hydrological and economic models of flood risk estimation, on one side, and investigate the impact of socio-cognitive processes on a large scale, on the other side.

## 4. The present research

The present research aims to highlight the importance of integrating a socio-psychological perspective in flood risk analysis and management, focusing on the impact of past experience and subjective risk perception on mitigation behavior and its consequent effect on expected flood risk and economic losses.

First, we investigated how near-misses regarding flood events can affect intentions to adopt private protective measures, such as insurance purchasing. Specifically, in line with the literature on the near-miss effect (e.g., [11]), we expect the individuals presented with a near-miss scenario to perceive a lower risk level than people who are not exposed to the same hazardous scenario. Crucially, we intended to explore the robustness of this effect by assessing whether it also arises among inhabitants of a flood-prone area, who have a high level of familiarity and personal experience with the negative consequences of floods. More specifically, if the effect of near-misses is stronger than the influence of past experience, a significant impact of near-miss events on risk perception should be observed among participants living both in flood-prone and safe areas (*Hypothesis 1a*).

As a consequence of risk perception reduction, in line with the literature [26,30,71], we hypothesized a decrease in individuals' intentions to adopt mitigation measures against flood damages, including the purchase of flood insurance, via a reduced perception of possible damages due to the adverse events (*Hypothesis 1b*).

In implementing our ABMs, our overarching goal was to propose a procedure to model personal mitigation behaviors in ABMs starting from survey data about individuals' intention to perform such behaviors. In particular, we focused on flood insurance purchasing as a private mitigation measure, since this action likely reduces financial consequences for people once a flood occurs [7]. At a more specific level, we tested whether, compared to a purely engineering model, ABMs including psychological variables would actually produce significantly lower estimates of economic losses for individual households, due to their adoption of flood-mitigation measures (*Hypothesis 2)*.

## 5. Study 1

In Study 1, *Hypothesis 1a* and *1b* were tested. We employed a real near-miss flooding scenario as an experimental manipulation delivered to inhabitants of both flood-prone and safe areas; then, flood risk perception, potential damage perception, and behavioral intentions to mitigate damages were assessed.

### 5.1. Case study area

The Seveso River rises in the northern Lombardy region of Italy, near the Swiss border. Its course is 52 km long, with a river basin 227 $km^2$ wide, and develops entirely in Lombardy, flowing downstream through northern municipalities of the Metropolitan City of Milan. When its course reaches the border between the municipal territories of Bresso and Milan, it is channeled in an underground canal crossing northern Milan districts for about 5,7 km, eventually flowing into the Martesana canal.

The increasing urban development in the municipalities upstream of Milan caused progressive sealing of vast areas and reduced the Seveso drainage capacity. Moreover, when entering Milan, the conveyance capacity of underground watercourse is critically reduced (reduced capacity is estimated at 30–40 $m^3/s$). The river is also a collection point for urban runoff networks. Rainwater collected by sewer systems reaches the stream much faster than in natural basins. The hydraulic capacity is barely sufficient for the drainage of urban rainwater of Milan hinterland, even in absence of inflows from upstream (for further details, see the Seveso hydrogeological structure master plan, [72]).

When heavy precipitations occur, the river cannot accommodate strong water flows from tributary streams and sewer systems, thus its water levels can rise very rapidly. Consequently, many circumscribed areas of the territory along its course are repeatedly exposed to urban flash flooding events. In northern Milan, in particular in Niguarda district, the river flows out from underground wells, causing recurrent urban flash floods (see Fig. 1; see the link under Data availability section for higher resolution and full Seveso course maps). Regional agencies responsible for monitoring hydro-meteorological processes regularly provide localized weather alerts to inform people about the risk of being exposed to flood hazard.

According to available data, from 1976 to 2016, 104 floods occurred in Milan (2.6 average occurrences per year). In recent years, 2010 and 2014 have been particularly critical, since 8 floods occurred during both years, some of which were particularly serious, with maximum flow rates close to 100 years return time (peak flood discharge 140–160 $m^3/s$). Floods impact in Milan may entail damages to and costs for infrastructures (e.g., subway, tramlines) and properties (e.g., shops, houses) in the order of millions of euros.

Crucially, data collection for this study started following a precise event involving the Seveso River area that can be classified as a near-miss. In the period between October 26th and November 3rd, 2018, many regions of Italy were affected by extraordinary severe weather conditions. An extremely intense Mediterranean cyclone, named as Vaia storm, brought intense precipitation and strong winds causing floods, landslides and consequent extensive damages to forest and urban areas [73]. Heavy rainfalls hit the northern areas of Italy, including the Metropolitan City of Milan. Despite these exceptional weather events, the flooding of the Seveso River did not occur.

Considering the peculiar hazardous scenario, in which the cyclone hazard affected the majority of northern regions of Italy and flood hazard hit nearby regions with spatial and temporal (and likely psychological) proximity to Milan; and taking into account that heavy rainfall in Milan are recurrently associated with Seveso flood hazard, it is possible to configure these circumstances (heavy rainfall, but absence of flash flooding and therefore damages) as a near-miss event. It was reasonably possible that the Seveso River would suddenly overflow and cause, as frequently does, damages to urban areas; however, these negative outcomes failed to materialize because of chance.

### 5.2. Participants and sampling

A total of 400 individuals were recruited to participate in a survey study. The answers of participants who completed at least the questions concerning flood risk and damage perception were eligible for statistical analyses. Participants declaring ambiguously their place of residence were excluded. The final sample comprised 241 Italian participants (189 women; $M_{age}$ = 44.07, $SD_{age}$ = 12.68; range: 18–80), of whom 151 live in areas affected by river floods along the course of the Seveso River, predominantly in Niguarda district (about 36,000 residents) and Bresso municipality (about 26,000 residents). The other 90 individuals mainly live in other districts of Milan that are not impacted by floods.

The first part of the sample was reached through posts on neighborhood-themed Facebook groups run by inhabitants of hazard-prone districts affected by the Seveso floods. The other part of the sample included people contacted through Facebook groups of the

**Fig. 1.** Upper (on the left) and lower (on the right) areas of northern Milan affected by floods (adapted from [72]).

southern districts of Milan unaffected by flood hazard. The posted messages included a link to Qualtrics, a software to run online surveys.

We ran a sensitivity power analysis for effect size estimation using GPower 3.1 software [74]. The power analysis for a 2 (Area of residence: *flood-prone* vs. *safe*) X 2 (Experimental condition: *near-miss* vs. *control*) between-subject experimental design suggested we were able to detect a small-to-medium interaction effect size $f = 0.18$ ($n = 241$, $alpha = .05$, $power = .80$).

### 5.3. Procedure and measures

The study was conducted following the ethical standards of the Declaration of Helsinki. Participants were asked to answer a self-report questionnaire. First, they completed the informed consent form and demographic questions, including an open-ended question inquiring the participants' place of residence in Milan and surroundings, subsequently coded by authors as *flood-prone* vs. *safe* areas. Then, respondents were randomly assigned to one of two experimental conditions (*near-miss* vs. *control*).

The experimental manipulation consisted of a brief text. In both conditions, the text introduced the participants to a geographical description of the Seveso River and its historical issue of recurrent floods in case of heavy precipitation. In the *near-miss* condition, in line with what happened in the region at the time, the textual manipulation continued highlighting the fact that the Seveso River did not overflow, despite the strongly severe weather that caused disasters in many other close areas of Italy. A picture of the dry riverbed taken in that period was also shown. In the text read by the participants in the *control* condition, no further information was provided; instead, a map of the course of the Seveso River was shown after the introductory paragraph. After the manipulation, participants were asked to fill out a questionnaire assessing Risk Perception, Damage Perception, and Personal Mitigation Intentions (see the full survey at the link under Data availability section).

The Risk Perception scale was measured through two ad-hoc items (Cronbach's $\alpha = .75$) concerning the perceived frequency of flood occurrence (i.e., "*I* believe *that over the coming years the Seveso floods will be more frequent*") and the perceived probability of a future flooding event (i.e., "*I believe that the Seveso River is likely to overflow the next time heavy rainfalls occur*").

The Damage Perception scale consisted of eight ad-hoc items (Cronbach's $\alpha = 0.86$) assessing the perceived probability of future floods causing negative consequences to people, private properties, and public infrastructures and areas (e.g., "*In the event of a flood, I think it is likely that my home (rooms, garage, basement …) will be damaged*").

The Personal Mitigation Intentions scale was composed of nine ad-hoc items (Cronbach's $\alpha = 0.84$) related to the individuals' intentions to adopt preventive measures to reduce the damages to their properties due to floods (e.g., "*I intend to make changes to my home to make it safer in case of flooding*"). This scale included an item on the intention to purchase insurance against flood damages ("*I am likely to invest money in insurance for damage to my home caused by flooding*"), upon which the parameters of the ABMs were implemented in Study 2. Participants responded to all questions on a 7-point scale ranging from 1 (*I totally disagree*) to 7 (*I totally agree*).

### 5.4. Analyses plan

To test *Hypothesis 1a*, a series of 2 (Area of residence: *flood-prone* vs. *safe*) X 2 (Experimental condition: *near-miss* vs. *control*) between-participants ANOVAs were performed on the following dependent variables: Risk Perception, Damage Perception, Personal Mitigation Intentions, and then, separately, on the single item of intention to purchase insurance against flood damages, which is part of the Personal Mitigation Intentions scale.

To test *Hypothesis 1b*, we computed two sequential mediation models testing the effect of the experimental condition (near-miss vs. control) on mitigation intentions through risk and damage perception (PROCESS, Model 6, 5000 bootstrap resampling; [75]). In the models (see Fig. 2), the independent variable was the experimental condition (0 = *control*; 1 = *near-miss*), Risk Perception and Damage Perception were sequential mediators, and Personal Mitigation Intentions (or the single item on intention to purchase insurance) were the dependent variable.

### 5.5. Results

The ANOVA on Risk Perception showed a significant main effect of the experimental condition, $F(1, 237) = 7.17$, $p = .008$, $\eta^2_p = .03$ (see Table 1 for descriptive statistics). In line with *Hypothesis 1a*, participants who received near-miss information reported lower levels of perceived risk ($M = 3.92$, $SD = 1.47$) than did participants in control condition ($M = 4.47$, $SD = 1.44$). However, the ANOVA yielded neither the main effect of area of residence, $F(1, 237) = 1.50$, $p = .221$, $\eta^2_p = .006$, nor the interaction effect, $F(1, 237) = 0.64$, $p = .42$, $\eta^2_p = .003$. Thus, the effect of the near-miss proved to be robust across residence areas and unaffected by the level of familiarity with flood risk. By contrast, the analyses carried out on Damage Perception, Personal Mitigation Intentions, and the item regarding the intention to purchase insurance showed only a significant main effect of area of residence on Personal Mit-

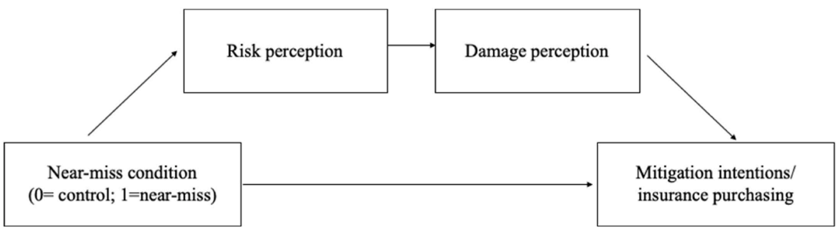


**Fig. 2.** A conceptual model of the sequential mediations.

**Table 1**
Means (SDs) of Risk Perception, Damage Perception, Personal Mitigation Intentions, and intention to purchase insurance split by experimental condition and area of residence.

| Experimental condition | Area of residence | Risk Perception | Damage Perception | Personal Mitigation | Insurance purchase |
|---|---|---|---|---|---|
| Near-miss | Flood-prone | 3.77 (1.42) | 3.65 (1.29) | 3.04 (1.30) | 2.08 (1.61) |
| | Safe | 4.16 (1.53) | 3.67 (1.13) | 2.42 (1.14) | 1.78 (1.22) |
| Control | Flood-prone | 4.44 (1.47) | 4.06 (1.26) | 2.99 (1.21) | 2.40 (1.84) |
| | Safe | 4.52 (1.41) | 3.73 (1.09) | 2.66 (1.21) | 2.24 (1.81) |

igation Intentions, $F(1, 227) = 7.88$, $p = .005$, $\eta^2_p = .03$. Participants in flood-prone areas were more prone to adopt mitigation strategies ($M = 3.01$, $SD = 1.25$) than participants in safe areas ($M = 2.54$, $SD = 1.17$). The analyses did not reveal any other significant effect, $F\text{s} < 2.96$, $p\text{s} > .087$.

In line with the ANOVA that did not show a significant interaction between the near-miss condition and the area of residence, a moderation model exploring the interaction between experimental condition and area of residence on risk perception proved to be non-significant, $\beta = -0.31$, SE = 0.39, $t = -0.80$, $p = .42$, 95% CI[-1.07, 0.45]. Thus, before computing mediation models, data was collapsed across risky and safe zones.

The mediation model including the composite score of Personal Mitigation Intentions as dependent variable yielded a significant effect of experimental condition on the first mediator, Risk Perception (see Table 2 for estimates). Then, entering experimental condition and Risk Perception on the second mediator, i.e. Damage Perception, only Risk Perception proved to have a significant effect. Moreover, controlling for experimental condition and Risk Perception, Damage Perception significantly affected Personal Mitigation Intentions. Ultimately, the total indirect effect proved to be significant, $\beta = -0.17$, SE = 0.06, 95% CI [ −0.30, −0.06].

The same mediation model carried out with the single item of insurance purchase intentions as dependent variable revealed the same pattern (see Table 3 for estimates). Experimental condition significantly predicted Risk Perception, whereas controlling for experimental condition and Risk Perception, Damage Perception significantly affected intention to purchase insurance. The total indirect effect also proved to be significant, $\beta = -0.13$, SE = 0.06, 95% CI [ −0.26, −0.04].

Therefore, as shown by the mediation models and in line with *Hypothesis 1b*, the near-miss event is likely to reduce flood risk perception that, in turn, decreases the prediction of future damages and, consequently, intentions to adopt personal mitigation strategies such as purchasing flood insurance.

## 6. Study 2

In Study 2, we propose a survey-based procedure to model agents' behaviors in ABMs using data about intentions to perform such behaviors. As a case study, we considered the effect of near-miss events over the intention to purchase insurance against flood-related damages. Specifically, we intended to assess the impact of including this psychological factor on the predicted damages of an area and whether the procedure proposed was able to properly capture the near-miss effect observed in Study 1. To do so, we developed and compared four different ABMs (for further details, see the ODD protocol provided with simulation datasets and analyses script at the link under Data availability section).

**Table 2**
Effects for each path of the mediation model with Personal Mitigation Intentions as dependent variable.

| Effect type | Model | Estimate | SE | $t$ | $p$ | 95% CI | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower | Upper |
| Direct | Near-miss condition ⇒ Mitigation intentions | .13 | .13 | 1.00 | .317 | −.13 | .39 |
| Component | Near-miss condition ⇒ Risk perception | −.60 | .19 | −3.13 | .002 | −.97 | −.22 |
| | Risk perception ⇒ Damage perception | .48 | .04 | 10.49 | <.001 | .39 | .57 |
| | Damage perception ⇒ Mitigation intentions | .59 | .06 | 9.26 | <.001 | .47 | .72 |
| Indirect | Near-miss condition ⇒ Risk perception ⇒ Damage perception ⇒ Mitigation intentions | −.17 | .06 | n.a. | n.a. | −.30 | −.06 |

**Table 3**
Effects for each path of the mediation model with insurance purchase intentions as dependent variable.

| Effect type | Model | Estimate | SE | $t$ | $p$ | 95% CI | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower | Upper |
| Direct | Near-miss condition ⇒ Insurance intentions | −.25 | .21 | −1.18 | .239 | −.66 | .17 |
| Component | Near-miss condition ⇒ Risk perception | −.60 | .19 | −3.13 | .002 | −.98 | −.22 |
| | Risk perception ⇒ Damage perception | .48 | .05 | 10.48 | <.001 | .39 | .60 |
| | Damage perception ⇒ Insurance intentions | .45 | .10 | 4.40 | <.001 | .25 | .66 |
| Indirect | Near-miss condition ⇒ Risk perception ⇒ Damage perception ⇒ Insurance intentions | −.13 | .06 | n.a. | n.a. | −.26 | −.04 |

### 6.1. Agent-based models description

#### 6.1.1. Shared features

The model by [65], and specifically its flood risk submodel, was used as a starting point for implementing all our ABMs. The model is implemented in NetLogo [76] and can provide flood risk estimations for a neighborhood that includes different land-use areas, such as private households. Our aim, rather than faithfully modeling the dynamics of a specific neighborhood, was to characterize agents' behavior affected by the near-miss effect in ABMs using survey data; thus, the neighborhood represented in the model could be considered as a hypothetical, generic location close to a hydrographic basin.

The submodel estimates the economic flood risk of the target neighborhood by computing its expected annual damage (EAD, expressed as euro/year), that is, the amount of economic losses that the neighborhood is likely to suffer in a year due to floods. To compute the EAD, the model simulates six possible inundation scenarios with different levels of severity (determined by the extension of the area interested by the flood and water depth) and different probabilities of occurring. Then, considering variables such as the elevation (i.e., the height over the sea-level) and the value of buildings, the predictions of damage for every scenario are integrated into the overall EAD measure (for further details about the procedure to compute the EAD, see the ODD protocol and [65]). In our work, we focused on the cells representing private households since we were interested in modeling private mitigation intentions, specifically about insurance purchasing.

Building on this flood risk estimation model, three psychologically grounded ABMs were implemented. In all those ABMs, the hypothetical population considered consisted of 1615 households, a number that resulted from initializing each residential cell in the models as a single household. These households were then subjected to an insurance-purchasing process composed by the following steps.

First, each household received a personal mitigation score representing their intention to purchase insurance against flood-related damages. These scores were randomly drawn from a normal distribution based on the mean and standard deviations of the item assessing insurance purchasing intentions in Study 1. Then, the personal mitigation scores assigned to the households were transformed into a probability of purchasing the insurance, and based on this probability each agent was assigned the status of either "insured" or "non-insured". Finally, for all those households resulting as insured at the end of the process, the EADs they would have suffered based on the computation of the flood risk submodel were multiplied by a factor of 0.005 (damage reduction parameter). This enabled the model to simultaneously account for the insurance cost and the amount of money refunded: for example, a household experiencing damages for a total of 100,000 euros would end up sustaining a loss of 500 euros, which would represent the cost of the insurance covering that amount of damage (for further details, see the ODD protocol).

#### 6.1.2. Distinguishing features

As mentioned above, the four ABMs shared the same basic computation of the EAD and, for the three psychological models, the same core steps of the insurance-purchasing process. Here are discussed the characteristics that differentiated each model.

*6.1.2.1. Basic model.* It represents a purely engineering model used to estimate the flood risk of an urban area, based exclusively on hydrogeological and economic variables. In this model, the insurance purchasing pipeline is not integrated, and there are no stochastic elements in the risk estimation process (thus, each of its runs produces the same EAD value). This model was used as a benchmark to show how the predicted economic damages can actually differ once individuals' intentions to purchase insurance are considered, as in the three psychologically refined models presented below.

*6.1.2.2. Control ABM.* This model integrates the insurance purchasing process, parametrizing it on the general population who does not have experience with natural hazards. In particular, in the control ABM the mean and standard deviation used to create the distribution of personal mitigation scores were based on the participants belonging to the control condition and safe area group in Study 1 ($M = 2.24$, $SD = 1.81$).

*6.1.2.3. Near-miss (NM) ABM.* This model aimed to assess the impact of the experience with a near-miss event on people's motivation to purchase insurance and, consequently, on the EAD of the area. The NM model is analogous to the Control one, but the mean and standard deviation of the personal mitigation scores distribution were based on the participants belonging to the experimental condition and flood-prone area group in Study 1 ($M = 2.08$, $SD = 1.61$).

*6.1.2.4. Descriptive norms (DN) ABM.* The fourth ABM considers that individuals' behavior cannot be fully understood in isolation, especially during collective negative events like disasters. Thus, it includes the possibility that a household is affected by the most widely shared thoughts and accepted behaviors among their group of reference, that is, by descriptive norms [77–79]. Indeed, prior empirical research revealed that descriptive norms play a critical role in determining people's behavior both before and during a hazard. In case of natural hazards, descriptive norms can affect coping appraisal (e.g., [69,80]), which represents individuals' evaluation of possible actions in response to the perceived threat and of their ability to implement these responses, including purchasing insurance against flood-related damages.

The aim of the DN model was to explore how descriptive norms can interact with the near-miss effect in determining individuals' level of protection motivation. This model was identical to the NM model in its structure and in the values used to determine the personal mitigation scores distribution, but a social interaction procedure was added. First, after having assigned the personal mitigation scores, each household was grouped with other four agents to constitute the household's "social circle". The number four was selected as it appears to be an average quantity reported by people when asked to indicate the number of close friends they have (e.g., [81–85]; see also [86–88]).

Each household then compared its own mitigation score with the average score of its social circle, increasing or decreasing its score by a certain "amount of change" value if it resulted lower or higher compared to that of its circle. The comparison and adjustment between the agent's and its group's score were iterated four times, representing repeated interactions among neighbors. After the fourth iteration, the resulting personal mitigation scores were used to determine the households' probability of purchasing the insurance (see the ODD protocol for further details on the social interaction process).

The three psychologically grounded models (Control, NM, DM) present a certain degree of randomness, for example, in terms of the number of insured agents and their location in the neighborhood, which changed at every run of the model. Therefore, to perform the necessary analyses to test our hypotheses, we ran the three models 100 times (see Fig. 3 for a conceptual representation of the ABMs flow).

### 6.2. Analyses plan

First, to check that the models produced sensible results, the correlation between the number of insured agents and EAD was computed for the Control, NM, and DN models, in order to ascertain that higher numbers of insured agents corresponded to lower EAD estimates. Then, to test *Hypothesis 2*, a series of one-sample *t*-tests was run, comparing the EAD estimated by the Basic model with the values estimated by the three psychological models. The EAD produced by the Control, NM, and DN models were compared through a one-way ANOVA to assess whether the procedure successfully captured the near-miss effect found in Study 1, i.e., whether it produced higher expected damages for the NM and DN models compared to the Control model.

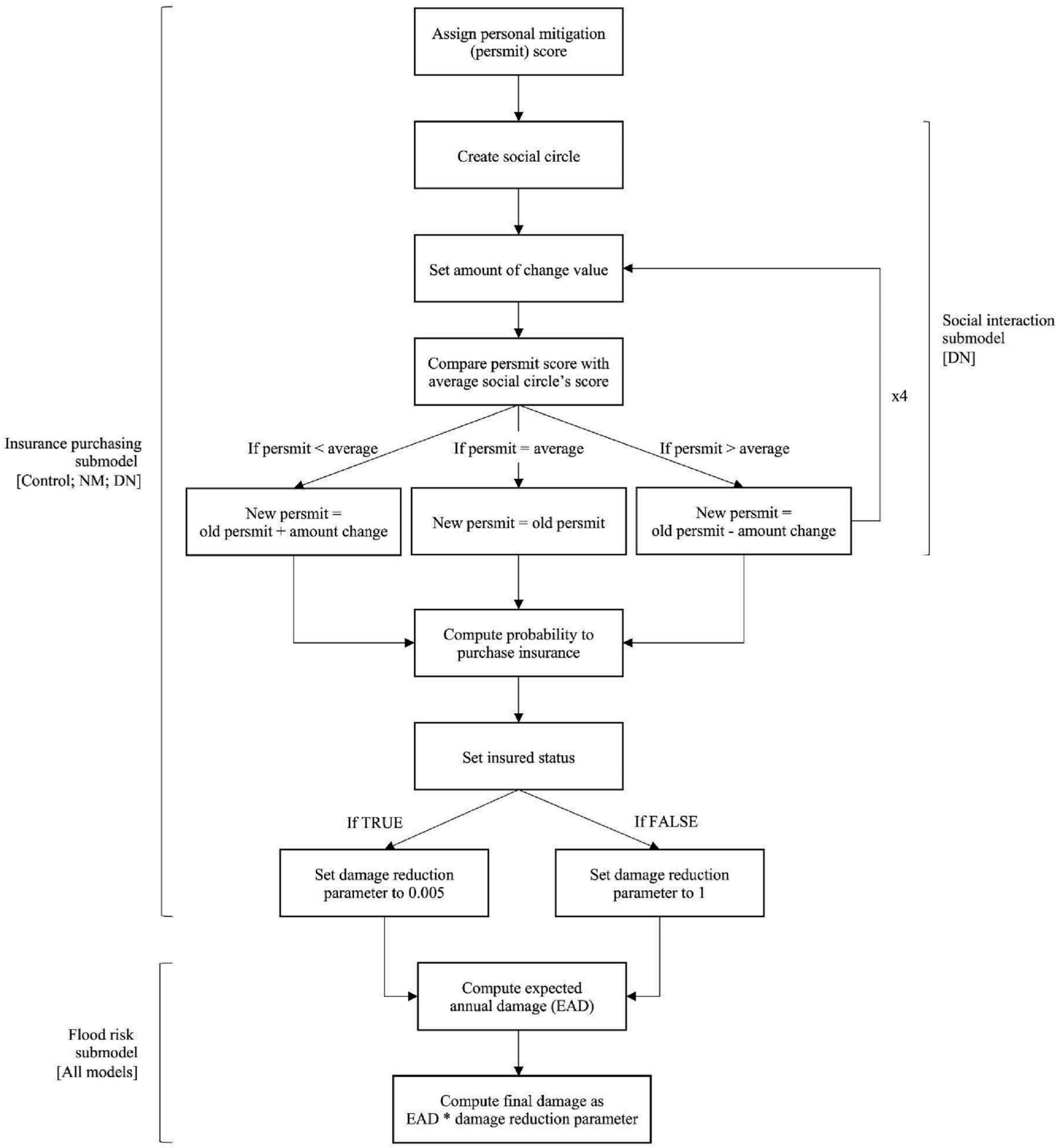


**Fig. 3.** Graphical representation of the submodels implemented in the ABMs (described from the perspective of the models' artificial households). The ABMs in which a specific submodel was included are reported between square brackets.

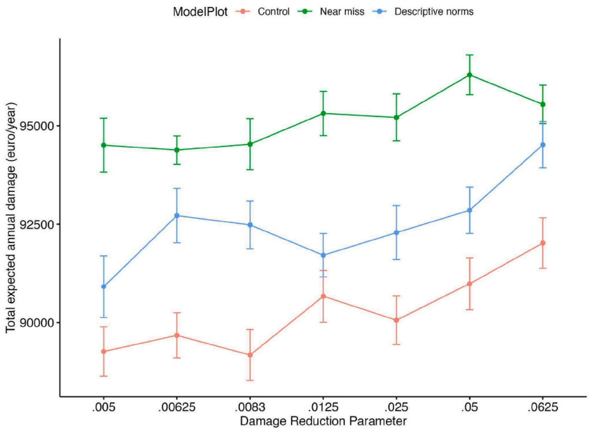


**Fig. 4.** Means (SDs) of the EAD in the three psychological ABMs as the damage reduction parameter varies.

These analyses were further integrated with a series of sensitivity analyses to better understand the behavior of the three psychological ABMs when changes to their non-empirically estimated parameters were considered.

### 6.3. Results

In the Control, NM and DN models, the number of insured agents were negatively correlated with the EAD values computed, confirming that the models were functioning properly (Table 5; see Table 4 for descriptive data of the four models).

Then, the one-sample *t*-tests revealed that the Control, NM and DN models all estimated a significantly lower EAD compared to the basic model (Table 6). This result suggests that integrating psychological factors can significantly affect damage assessment, in line with *Hypothesis 2*.

Finally, the one-way ANOVA conducted to compare the EAD computed by the three psychological ABMs reported a significant effect of the model considered, $F(2, 297) = 59.85$, $p < .001$, $\eta^2_p = .29$, with post-hoc comparisons (Bonferroni corrected) revealing that the models all significantly differed from one another on this variable (all *ps* $< .001$). Therefore, in line with Study 1, the output of the ABMs confirmed the negative impact of the near-miss experience on mitigation also at a large scale, given that the mean EAD of the NM model was significantly higher compared to that of the Control one. Furthermore, the fact that the DN model returned a lower EAD compared to the NM one suggests that social interactions might be able to moderate the negative influence of the near-miss effect.

**Table 4**
Mean and SD of expected annual damage (EAD, measured as euro/year) and the number of insured agents for each model.

| Model | Mean EAD | SD EAD | Mean Insured | SD Insured |
|---|---|---|---|---|
| Basic | 133,266 | 0 | 0 | 0 |
| Control | 89,397 | 3101 | 531 | 18.1 |
| NM | 94,336 | 2890 | 475 | 14.4 |
| DN | 91,971 | 3553 | 500 | 22.2 |

**Table 5**
Results of the correlation between number of insured agents and expected annual damage in the three psychologically grounded models.

| Model | *R* | *df* | *p* | 95% CI | |
|---|---|---|---|---|---|
| | | | | Lower | Upper |
| Control | −.43 | 98 | <.001 | −.58 | −.25 |
| NM | −.27 | 98 | .01 | −.44 | −.08 |
| DN | −.52 | 98 | <.001 | −.65 | −.36 |

**Table 6**
Results of the one-sample *t*-tests comparing the EAD computed by the basic model with that resulting from psychologically grounded ones.

| Model | *t* | *df* | *p* | *d* | 95% CI | |
|---|---|---|---|---|---|---|
| | | | | | Lower | Upper |
| Control | −141.46 | 99 | <.001 | −14.15 | −16.17 | −12.12 |
| NM | −134.72 | 99 | <.001 | −13.47 | −15.40 | −11.54 |
| DN | −116.24 | 99 | <.001 | −11.62 | −13.30 | −9.95 |

### 6.4. Sensitivity analyses

An additional set of analyses was run to investigate the effects of the non-empirically estimated parameters in the psychological models: the damage reduction parameter for the insured agents (set to 0.005 in the models) and, in the DN model, the number of social interactions and the number of peers assigned to each household to form the social circles (both set to a value of 4). Since these parameters were not directly based on empirical data, it is important to understand how the models' predictions would change depending on these values. To this end, the parameters were systematically varied and, for each new value of the parameter considered, the ABMs were run 30 times.

In the first round of simulations, the damage reduction parameter was varied between 0.005 and 0.0625 (higher parameter values corresponding to lower reductions of the EAD). Then, a 3 (type of ABM: Control, NM, and DN) x 7 (damage reduction parameter: 7 levels from 0.005 to 0.0625) ANOVA was carried out on the EAD (Fig. 4). As expected, the analysis revealed a significant main effect of the damage reduction parameter in the direction of an increased EAD when the damage reduction parameter is set to higher values, $F(6, 609) = 5.47, p < .001, \eta^2_p = .05$. Additionally, it was found a significant main effect of the type of ABM, $F(2, 609) = 109.29$, $p < .001, \eta^2_p = .26$, while the interaction between the type of ABM and damage reduction parameter failed to reach significance, $F(12, 609) = 0.94, p = .51, \eta^2_p = .02$. This indicates that the three models were affected in the same way by different levels of the parameter, thus suggesting a certain robustness of our results in this respect.

In the second round of simulations, the number of the social iterations and the size of the social circle in the DN model were both varied orthogonally between 1 and 7 (i.e., a reasonable size of the inner circle characterized by significant relationships; see above). Then, through a series of correlation analyses (see Table 7), we explored the relationship between the manipulation of these parameters and the number of insured agents identified by the model that, in turn, determines the EAD (the damage reduction parameter used for this analysis of the DN model was the original one of 0.005).

A greater number of repeated interactions appeared to result in a higher likelihood of agents' purchasing the insurance, with a consequent reduction of the EAD, while these values appeared to be only weakly correlated with the social circle size. Thus, it appears that the iteration parameter has a significant impact on the models' predictions and EAD estimations, moderating the negative impact of the near-miss effect. Therefore, these results warrant further empirical investigation to understand which are the optimal values for the iteration (and, possibly, the social circle size) parameters, and how to better model them within ABMs.

## 7. General discussion

Across two studies focused on the effect of flood near-misses over protection motivation [11,66], we found consistent support to our hypotheses.

Study 1 replicated in an ecological setting the near-miss effect: having information about the fortuitous avoidance of a river flooding is likely to weaken risk perception, expressed in terms of the perceived probability of future floods occurrence. Crucially, although a part of the literature reveals that risk perception is not necessarily associated with undertaking preventive measures ("risk perception paradox", [30]), our results suggest that risk perception fosters private precautionary behavioral intentions (including insurance purchasing) through the mediation of the perceived possibility of future damages ("motivational hypothesis", [89]). Moreover, extending prior studies on the association between risk perception and past experience [24,32,33], near-miss information proved to exert a negative effect even among inhabitants of a flood-prone area with significant and recurrent previous experience with hazard. Thus, the experimental study supports previous findings in a real-world scenario and directly investigates the unexplored interaction between the near-miss effect and past experience.

In Study 2, we proposed a possible procedure to model agents' behavior starting from survey data about the intention to perform such behaviors. More specifically, we focused on including the effect of near-misses over insurance purchasing intentions in models of flood risk estimation, parametrizing the procedure upon data collected among individuals living in flood-prone areas.

The results of the ABMs showed that models integrating psychological variables produce damage estimates that are significantly different from models disregarding these factors, thus confirming the possible impact of near-miss experience at a large population scale and the importance of accounting for human behavior when computing flood risk. Indeed, model comparison revealed that a population affected by a near-miss event might behave differently from the general population and could be prone to risk underestimation. Additionally, the models appeared to suggest that social interactions and descriptive norms might partially mitigate the negative effect of near-misses on individuals' intention to enact protective behaviors, and consequently on the economic damage they are expected to suffer personally. This result highlights that integrating parameters based solely on individual psychological processes

**Table 7**
Results of the correlation between the two parameters characterizing the social interaction process (i.e., number of interactions and size of the social circle) and the two main variables of interest of the DN model (difference in the number of agents insured before and after the social interaction process and the final expected annual damage).

| Parameter | Variable considered | *r* | *df* | P | 95% CI | |
|---|---|---|---|---|---|---|
| | | | | | Lower | Upper |
| Number of interactions | Difference insured | .61 | 1468 | <.001 | .57 | .64 |
| | EAD | −.43 | 1468 | <.001 | −.47 | −.39 |
| Social circle size | Difference insured | .07 | 1468 | .01 | .02 | .12 |
| | EAD | −.04 | 1468 | .09 | −.09 | .01 |

might not be enough, and more attention should be devoted to understanding how agents in a flood-prone area interact with one another over time.

The research has some limitations that open several avenues for future research. Some points were left unexplored regarding the effect of past experiences on protective behavior. For example, in our studies, we used measures (and scores) of intentions to adopt protective behavior. Still, there might be discrepancies between the intention to perform a behavior and its actual implementation [90]. Importantly, to test our hypotheses through a controlled experimental design, we necessarily had to simplify the scenario and focus the attention on specific cognitive factors. However, to capture the complexity of the phenomena, adopting a more integrative approach is of critical relevance. Indeed, it would be fruitful to consider not only cognitive factors but also the interplay between individual's cognition, motivations and emotions [91]. There are also different individual variables, such as the perceiver's competence, expertise, knowledge, trust in science and institutions that might forge the process and work as moderators [92]. Moreover, more comprehensive models should investigate the relationship between individual psychological variables and cultural, societal and institutional processes. Especially in risk-prone areas, governments, policy-makers and governmental agencies play a crucial role in raising awareness, promoting effective mitigation strategies, and advancing adaptation [93]. Within a specific cultural and political framework, these institutional actions are likely to forge risk perception and consequent population behaviors in the event of floods.

A further limitation of our research concerns the developed ABMs that are far from the state of the art of models of flood risk estimation. First, many aspects are simplified, either from the hydrogeological (for example, the water flooding is not represented dynamically) and the economic perspective (especially about the insurance-purchasing process). For instance, only private households were considered, but in case of floods, firms and public facilities as well often suffer severe damages. Moreover, we considered a single mitigation action (insurance purchase), disregarding the impact of different prevention measures (e.g., using protective sandbags) and behaviors that might be implemented during the emergency (e.g., evacuation), as well as their interaction. In addition, in our DN model, the social interaction component was not empirically grounded. For example, the agents constituting the individuals' social circle were assigned randomly from the overall population, but it is more likely that people will tend to group and be influenced by similarly oriented individuals (e.g., [94]), with analogous levels of protection motivation. Future studies might try to estimate the parameters necessary to model the social interaction component directly among populations of interest, to increase the validity of the models' estimates.

Despite these limitations, the current research has important implications. To our knowledge, it is one of the first attempts to integrate the effect of near-miss events in flood risk estimation models, using empirical data collected among a target population (for another work proposing the implementation of psychological theories into ABMs, see [95]). In general, ABMs grounded on psychological theories may have relevant implications since local and state authorities may use them as a tool to estimate the efficacy of possible policies [96], and, for instance, to evaluate the efficacy of intervention and communication strategies. We are aware that our work does not analyze and test specific tools devised to prevent near-miss effects on people's decision making. However, identifying and analyzing critical psychological processes likely to affect risk perception and behavioral mitigation intentions is a first preliminary but essential step to develop appropriate decision aids.

Additionally, because of their characteristics, ABMs could be fruitfully employed to study with a new approach many phenomena of great interest for social psychologists [61], such as those that involve group processes (for some examples, see the works on group cooperation, [97]; and on group formation, [98]). These topics are usually studied by focusing on the individual level, failing to consider the complex dynamics that emerge at the higher group level [60]. Therefore, making efforts to increase and standardize the implementation of ABMs based on the results of classical psychological studies is an interesting and important avenue of research in the future, for its theoretical importance for the discipline and its applied value in all those scenarios in which the human factor is critical.

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## Declaration of competing interest

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

## Data availability

Additional materials are provided including: Study 1 full survey; Study 1 dataset and variables definitions; ODD protocol; Study 2 analyses script; Study 2 simulation datasets; statistical symbols definitions; and Seveso River flood maps. Materials are available on OSF repository at the following link: https://osf.io/hrjsb/

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