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ORIGINAL PAPER

Flood impacts on individual well-being: insights from a post-event survey across differently exposed groups in Marche region, Italy

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Abstract
In Europe, current flood risk assessment practices often rely on the number of directly exposed residents as a proxy of the overall flood impact on people, thereby overlooking the broader range of flood consequences on human well-being. Literature studies have shown that these consequences encompass several direct and indirect intangible impacts and may affect people even beyond the flooded area. With aim of deepening current understanding of flood impacts on people, we developed a questionnaire that was distributed to the citizens of the Marche region of Italy affected by a severe flood in 2022, reaching 707 responses. Respondents were asked to self-identifying as belonging to one of three exposed groups: directly affected (e.g., experienced damage to their property), indirectly affected (e.g., family or friends experienced direct impacts, or experienced work or domestic system interruptions) and not affected. Respondents of these three exposed groups were asked to rate the severity of various impacts, as well as the overall impact they experienced. The responses were analysed through descriptive statistics and multiple linear regressions. The analyses allowed to understand, first, how severely each impact was perceived when considered independently, and second, the role of each impact types in relation with the overall flood impact. The results show that flood consequences are felt even outside the flooded area, and underline the central role of intangible impacts, specifically psychological ones, in shaping the overall impact across all the exposed groups. The findings presented support the implementation of more effective recovery policies and measures that prioritize the most significant impacts for differently exposed groups.

Keywords Flood risk · Human well-being · Exposed groups · Perceived impact perception · Marche region flood · Survey

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1 Introduction

The recent flood events in Europe, such as the 2021 flood in central Europe, the 2022 and 2023 floods in Italy and the devastating 2024 flood in Valencia, highlight the urgent need for effective flood risk management to predict and mitigate the negative consequences of floods (Thieken et al. 2023; Cremonini et al. 2024; De Lucia et al. 2024; Martin-Moreno et al. 2025). A deeper understating of flood impacts is crucial to this aim, to better inform both risk reduction policies and climate change adaptation strategies (Hudson et al. 2019a) especially considering the increasing frequency and intensity of extreme weather events (Alfieri et al. 2015; Robinson et al. 2021).

In this context, in Europe, member states are required to conduct a comprehensive flood risk assessment that accounts for people, the environment, cultural heritage, and economic activities under the European Flood Directive (2007/60/EC), as the basis of proper flood risk management plans. For what concerns people, even if the primary objective of flood risk management is to limit damage to them, available models for its assessment are scarce (Hudson et al. 2019b; Messner et al. 2007; Mishra et al. 2022) and member states often adopted, as a proxy for assessing damage to people, the number of potentially affected individuals, specifically those living in the flooded area. This is also the case in Italy, where the MOVIDA project (Modelli e strumenti per la valutazione integrata del danno—Models and tools for integrated damage assessment), that represents the most recent attempt to estimate flood damage across different assets, limits the estimation of damage to people to the number of exposed residents (Simonelli et al. 2022). While practical, this approach is unable to capture the full social and human impact of flooding. Accounting for the full range of impacts in risk estimate has been shown to be particularly important, as relying on partial assessments (i.e., accounting only for direct and tangible impacts) can lead to suboptimal decisions in flood risk management (Kreibich et al. 2014).

Considering also that the third Sustainable Development Goal (SDG) emphasizes the importance of ensuring healthy lives and promoting well-being for all (UN General Assembly 2015), it becomes imperative to develop better models for the estimation of damage to people. This requires better understanding the full range of impacts on population well-being and, accordingly, to identify the groups of people who are exposed to them.

In this context, the present manuscript addresses three research questions (RQs). First, how severely different flood impacts are perceived by people? (RQ1). Second, which is the role of different flood impacts with respect to the overall flood impact perceived by people? (RQ2). Third, do these impacts vary among differently exposed groups of society? (RQ3).

In the literature, the impacts of flooding are commonly categorized as direct versus indirect, and as tangible versus intangible (Penning-Rowsell and Fordham 1994; Smith and Ward 1998). Direct impacts result from the contact with flooding water, whereas indirect impacts occur in a different time and location from the flood event. Both direct and indirect impacts can be further distinguished in tangible, if they can be expressed in monetary values, and intangible, if they cannot be easily quantified in economic terms. For what concern flood impacts on population, they are commonly assessed as a direct intangible damage. This category is typically expressed in terms of fatalities, injuries, or, more broadly, the number of directly affected individuals (Doocy et al. 2013; Aceto et al. 2017). Numerous studies have focused on the circumstances and causes of fatalities (Jonkman and Kelman 2005; Salvati et al. 2018; Petrucci et al. 2019; Thieken et al. 2023) and predictive models have been developed (e.g., Jonkman et al. 2008; Terti et al. 2019; Alfieri et al. 2020; Yazdani et al. 2023). Nevertheless, research has shown that the consequences for affected people extend far beyond physical harm. Among direct intangible impacts, the loss of personal belongings of sentimental value, often referred to as memorabilia, has been shown to cause significant emotional distress and it can be perceived as more severe than tangible damages (Penning-Rowsell and Green 2000; Mishra et al. 2022). Likewise, psychological distress, included among indirect and intangible impacts, should be mentioned. Several studies have documented the negative mental health outcomes experienced by directly affected individuals, reporting symptoms such as post-traumatic stress disorder (PTSD), depression, and anxiety (Mason et al. 2010; Stanke et al. 2012; Fernandez et al. 2015; Golitaleb et al. 2022; Zenker et al. 2024; Bubeck et al. 2025), that can persist even years after the event (Di Fiorino 2005; Mulchandani et al. 2020). Moreover, flooding can also lead to additional indirect intangible effects such as a loss of community cohesion and trust in institutional bodies. Tapsell et al. (2002) and Butler et al. (2018) presented how, after a flood event, citizen can experience a deterioration of community life, a lack of confidence in the authorities' ability to manage future flood events and how this can negatively affect the mental health recovery.

While a broad range of impacts is shown to affect those who enter in contact with floodwater, some of these impacts can potentially affect also those who live outside the flooded area. Flood impacts can span across both time and space (Bubeck et al. 2017) and, therefore, individuals do not need to be directly exposed to flood to suffer from negative consequences (Hudson et al. 2019b). People may be impacted by the inaccessibility of infrastructure whose functionality is disrupted by the flood or experience the interruption of work activities (Menoni et al. 2016; Prall et al. 2024); the latter occurs when workplaces are flooded or become inaccessible because of road links interruption. These impacts can be categorized both as indirect tangible, as they can be quantified in term of loss of income or increased travel cost (Merz et al. 2010; Bubeck et al. 2017), and indirect intangible, as monetary loss is hardly able to capture the full extent of the discomfort caused to people. Human health consequences can also affect those residing outside the flooded area. As first aid and debris clean-up help are provided by networks of friends, family and neighbours (LaLone 2012), injuries may occur during these activities also to non-flooded people. Moreover, Montalti et al. (2024) documented the health impact of the 2023 flood in the Emilia-Romagna region in Italy, highlighting that, surprisingly, the incidence of dermatological, gastrointestinal, respiratory, conjunctivitis, otitis, and fever symptoms were significantly higher among individuals not exposed to floodwaters, compared to those directly exposed. Mental health issues can also be observed among this group of people. Peek-Asa et al. (2012) showed that work disruption, which can occur among non-flooded population groups, can increase the likelihood of reporting symptoms of PTSD while Carroll et al. (2010) reported that psychological stress is experienced also by workers supporting those affected in the aftermath of the flood. Fothergill et al. (2021) argued that floods can be traumatic even for those non-flooded as they can perceive the loss of the affected residents and project this situation onto themselves.

Building on the literature, in the present manuscript individuals are classified according to their exposure to floodwater and the type of impacts experienced. Individuals whose homes were flooded are referred to as directly affected. Individuals who did not experience direct contact with floodwater but were affected by indirect consequences of the flood, such as work interruption, disruption of household facilities, or having relatives or friends who were directly affected, are referred to as indirectly affected. Individuals who were neither directly nor indirectly affected by the flood are referred to as not affected in this paper.

To answer to the research questions, a questionnaire was designed and distributed to residents of the municipalities in the Marche region of Italy affected by the exceptional flood event of September 2022. The questionnaire targeted the three exposed groups discussed above (directly, indirectly and not affected people).

While recent studies in Italy have focused on flood risk perception and preparedness considering both flooded and non-flooded groups (see Zabini et al. 2021; Palazzoli et al. 2026), to the authors' knowledge, this study is among the first to assess the severity perception of different flood impacts in affected communities, distinguishing between directly, indirectly and not affected individuals. The findings obtained and presented here can help authorities to prioritise and differentiate support required for different groups of society in the aftermath of flood events, thereby increasing well-being for all and societal resilience. Further, findings can support damage modelers moving beyond tangible damage and encourage the development of models able to capture the most relevant types of impacts for different exposed groups, thus broadening the scope of flood risk assessments beyond the flooded area. This, in turn, can enable a more accurate and comprehensive flood risk estimate and management that prioritize the most significant impacts for each group.

2 Case study, data and methods

The research framework adopted in this manuscript is shown in Fig. 1. The whole research is based on a case study in the Marche Region (Central Italy) affected by a severe flood event that occurred in September 2022. Starting from the research questions (RQs), literature studies (cited in the Introduction section) have been investigated to identify flood impact types affecting different exposed groups of the society. The literature served to build a first conceptualization of these impacts with respect to the exposed groups and, thus, to design the questionnaire. Additionally, a field survey on damaged assets in the study area, contributed to the formulation of context-specific questions. The questionnaire was distributed via social media campaign and local newspaper to the population of Marche region.

The collected responses were analysed through two distinct methods, each addressing different RQs. First, descriptive statistics were used to explore the perceived severity of impacts across the various exposed groups, which provided answers to RQ1 and partially to RQ3. Second, multiple linear regression analyses were conducted using the overall perceived impact of the flood as the dependent variable. These analyses addressed RQ2 and further supported the answer to RQ3.

2.1 Case study

The analysis was conducted in the Marche Region (Central Italy) where a record-breaking rainfall event occurred in September 15th, 2022, causing widespread floods and severe impacts, including 12 fatalities, 1 missing person and several injured people. The event was triggered by a stationary "self-regenerating" thunderstorm system lasting several hours. The highest rainfall was recorded in the municipality of Cantiano, where rainfall reached 419 mm in 12 h, exceeding historical maxima by nearly 250% (for more information on

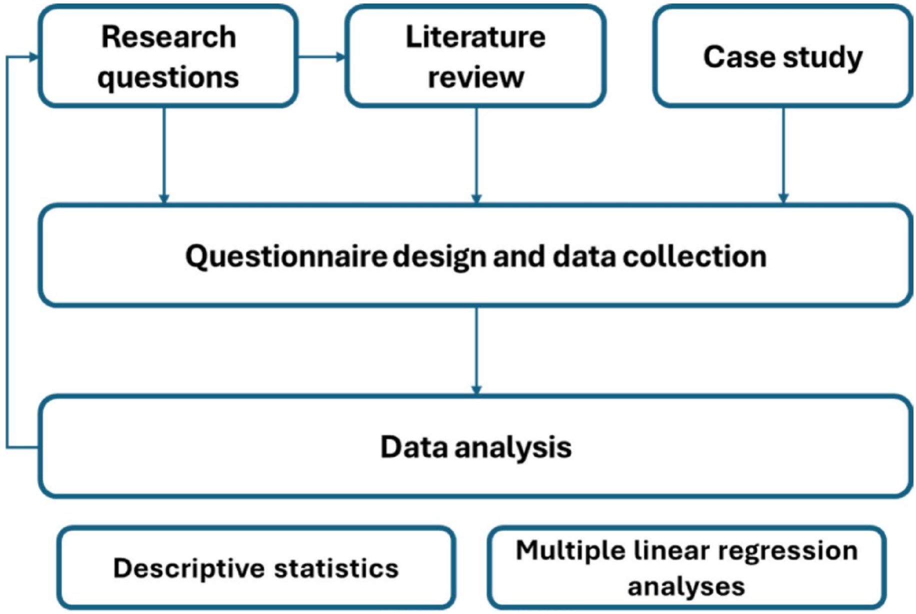

Fig. 1 Research framework

the event see De Lucia et al. (2024) and Santangelo et al. (2023)). The storm caused the flooding of multiple river basins in the region, including the Metauro, Cesano, Misa, Esino and Musone basins (see Fig. 2). Among these, the Misa basin experienced the most severe impacts (Corti et al. 2024), highly exceeding those of the last flood in the area in 2014.

Given the exceptional nature of the flood, different Italian universities volunteering mobilized in the months following the event to collect field data on the hazard and the related damage, to support the recovery and the reconstruction processes. Among them were the Politecnico di Milano and some of the authors of this paper, whose focus was on observed direct damage to buildings. Direct damage data collection was mostly carried out in the municipalities of Trecastelli, Ostra and Senigallia that were severely affected due to extensive flooding and intense sediment and trees transport from the river (Molinari et al. 2023). While the physical damage dataset created through the field survey (see De Lucia et al. 2024 and Rrokaj et al. 2025) was not used in the present analysis, the knowledge gained through the fieldwork provided researchers with deeper insights into the event and impacts differing across the study area. Accordingly, the municipalities of Trecastelli, Ostra, and Senigallia were also chosen to distribute the questionnaire, on which this study is based.

2.2 Questionnaire design and data collection

The questionnaire consisted of 62 questions and its completion lasted less than 12 min on average. It was designed to consider the three target groups of respondents: directly affected, indirectly affected and not affected. Each respondent was required to identify the group they belong to at the beginning of the questionnaire. Directly affected respondent group included people who experienced damage to their house. Indirectly affected respondents were those

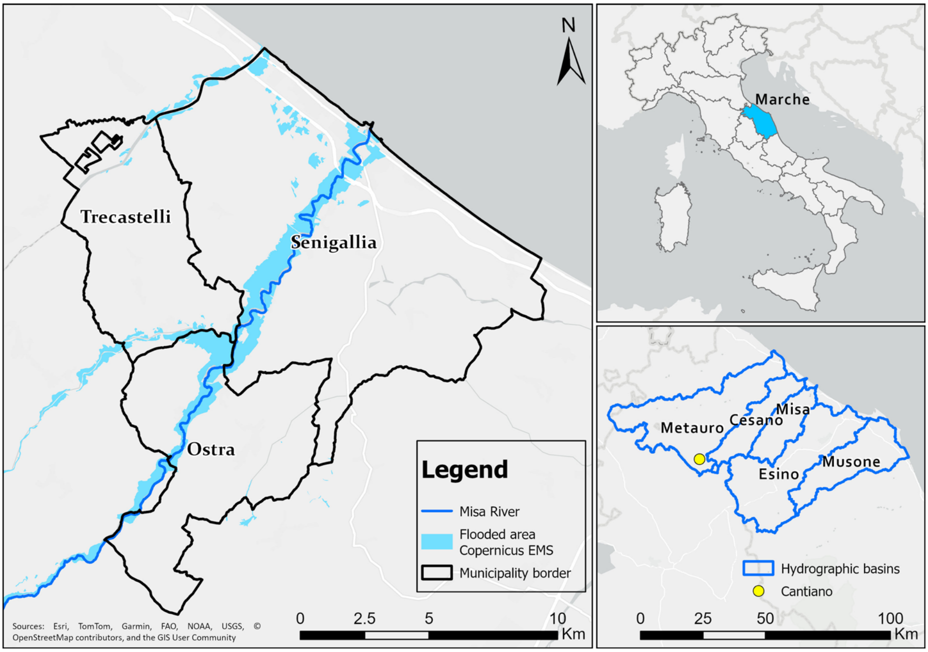

Fig. 2 Study area

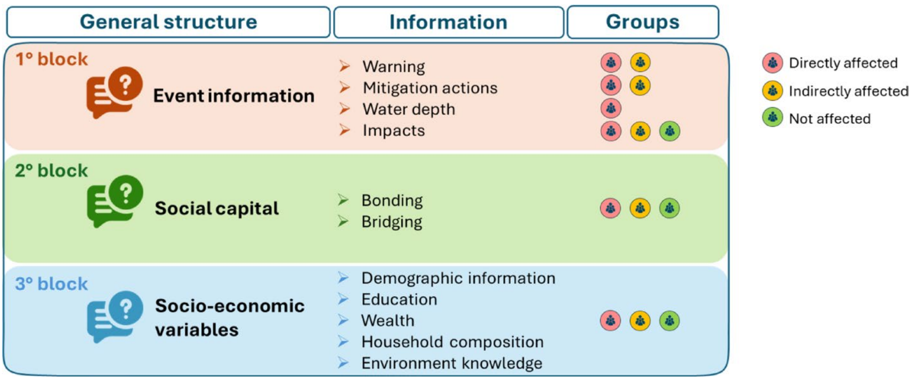

Fig. 3 General structure of the questionnaire, topics covered, and which groups answered which parts of the questionnaire

whose family or friends experienced direct impacts as well as those who experienced work interruption or interruption of domestic systems. Finally, not affected respondents were those who declared to have not been affected neither directly nor indirectly but still live in the Marche region.

The questionnaire structure followed the scheme of Fig. 3. It was composed by three consecutive blocks through which information on the event, the social capital and the socio-economic characteristics of respondents were collected. As shown in Fig. 3, certain questions were administered to respondents according to their group membership; therefore, not all questions were administered to all participants. It is worth noting that the questionnaire was designed to collect a broad range of information, with multiple purposes that go even beyond the scope of this manuscript, to optimise the data collection effort. The analysis presented in this manuscript focuses on the socio-demographic characteristics of the third block and on the impact section of the first block. The socio-demographic characteristics were analysed to detect potential bias in the sample by comparing respondents' characteristics with official statistics. The responses collected through the impact section were used to answer to the RQs. Specifically, the analysis was conducted on the responses of the perceived severity of impacts question shown in Table 1. In this question, respondents were required to rate, for each impact they experienced, how severely they perceived it, on a scale from 1 (very low) to 6 (very high). The option "I did not experience this impact" was also available. The impacts included in the question were building physical damage (BD), loss of memorabilia (LM), work interruption (WI), disruption or inaccessibility of infrastructure such as roads and railways (II), physical health impacts (HI), psychological impacts (PI), loss of trust in institutions (LT), and loss of community cohesion (LC). Lastly, a question on the overall personal impact (OI) was included, considering all the flood impacts experienced. In the multiple linear regression analysis presented later in this manuscript, OI was used as the dependent variable, while the different impact types were the independent variables. Moreover, an open question invited respondents to identify possible impacts not listed before (not showed in Table 1).

The questionnaire was developed in KoboToolbox, a free and open-source platform that allows users to create customized forms and surveys for data collection, as well as manage and visualize data. In the case of questionnaires, KoboToolbox enables its distribution to the target population through a simple direct link.

The data collection phase began on 23 April 2024, approximately 1 year and 8 months after the event, and lasted for one and a half months. During this period, the KoboToolbox link to the questionnaire was distributed through two main dissemination channels. First, the link was shared via articles published in online newspapers popular in the study area. A total of 6 articles were published containing the description, aim and scope of the project as well

Table 1 Extract from the questionnaire and translated to English: questions Q1 (a) to Q1 (i) on perceived severity of impacts

Variables	Q1. Please define, on a scale from 1 to 6, how bad (or unpleasant) the following types of impacts were for you personally: 1: Very low 6: Very high
BD	(a) Building physical damage
LM	(b) Loss of belongings of sentimental value
WI	(c) Work interruption
II	(d) Disruption or inaccessibility to services and infrastructure (such as roads, railways, etc.)
HI	(e) Physical health impact
LT	(f) Loss of trust in institution
LC	(g) Loss of community cohesion
PI	(h) Psychological impact
OI	(i) Define now, on a scale of 1 to 6, how severe you think the overall personal damage you suffered as a result of the September 2022 flood was for you. Please consider all direct and/or indirect damages suffered personally

as the link to the questionnaire. Second, a social media campaign was launched. The campaign, conducted on Meta for 20 days, enabled precise geotargeting to reach people within and in the surrounding of the affected areas. The ads were built with a brief description of the survey, the direct link to the KoboToolbox questionnaire, and pictures taken in the aftermath of the event depicting damaged assets. A total of 707 responses were collected through the questionnaire, with approximately half obtained through newspaper article publications and the other half through the social media campaign. Nine respondents did not provide any location information (e.g., province) and were therefore excluded from the subsequent analyses. Moreover, as 4 responses were considered unreliable from an internal check (not shown here), they were excluded from the analyses on the perceived severity of impacts.

2.3 Data analysis

2.3.1 Descriptive statistics: socio-demographic variables

To assess the representativeness of the sample with respect to the study area population, the demographic variables of gender and age were compared to the statistics of the study area provided by ISTAT (Istituto Nazionale di Statistica—National Institute of Statistics) in the 2021 census. All 698 responses considered were from people residing in the Marche region with 661 specifically in the municipalities of Senigallia, Ostra and Trecastelli. Therefore, comparisons were only possible for the three municipalities; the remaining data were too dispersed across the area to identify a comparative dataset. Comparisons were conducted for whole sample and for each exposed group.

2.3.2 Descriptive statistics: perceived severity of impacts

Descriptive statistics of perceived severity scores of flood impacts presented in Table 1 was performed for the whole sample and the three exposed groups. This analysis allowed to compare scores across different impact types and to identify how severely these impacts were perceived, thus addressing RQ1. Furthermore, by comparing severity scores across the exposed groups, the descriptive statistics contributed to answering RQ3. To perform the statistics, ordinal responses on impact severity were transformed into a continuous 7-point scale ranging from 0 to 6. Responses rated from 1 to 6 retained their original values, while the response "I did not experience this impact" was assigned a value of 0, to account for the absence of perceived impact.

Differences in perceived impact severity across exposure groups were also assessed using non-parametric Kruskal–Wallis tests. Where statistically significant differences were detected, pairwise comparisons of the mean ranks between groups were performed using the multiple comparison procedure for Kruskal–Wallis described by Siegel and Castellan (1988). Results of Kruskal–Wallis tests and the pairwise comparisons of mean ranks are reported in Tables S5 and S6, respectively, in the Supplementary Information.

2.3.3 Multiple linear regression

Four multiple regression analyses, one for the whole sample and one for each exposed group, were conducted on the responses collected through the questions (Q1) presented in

Table 1. The regressions aimed to find a relation between the overall impact (OI), i.e. the dependent variable, and the eight specific impacts (BD, LM, WI, II, HI, PI, LT, and LC) considered as independent variables. The results of the regressions specifically answered to RQ2 as they defined the role of different impact types with respect to the overall impact caused by a flood to individuals. Moreover, they further contributed to answering RQ3 as the analysis is performed for all groups.

All variables were treated as continuous, with values from 0 to 6, like in the previous analysis. The four multiple regression models adopted follow the general form of Eq. (1):

$$OI = \beta_0 + \beta_1 * BD + \beta_2 * LM + \beta_3 * WI + \beta_4 * II + \beta_5 * HI + \beta_6 * LT + \beta_7 * LC + \beta_8 * PI. \quad (1)$$

In each model, β_0 denotes the intercept, and β_1 through β_8 are the regression coefficients associated to the eight impact types.

Multicollinearity among predictors was assessed using tolerance statistics which is the reciprocal of the variance inflation factor (1/VIF). As recommended by (Menard 1995), predictors showing values of tolerance below 0.2 have been excluded from the regression models. VIF and tolerance statistics values, together with correlation matrix, for each group are provided in the Supplementary Information.

Starting from the complete multiple linear regression models represented by Eq. (1), a backward stepwise selection based on Akaike Information Criterion (AIC) was adopted to check robustness. This procedure allowed to provide parsimonious models and to compare them with the complete models. Accordingly, we compared complete and stepwise-selected models in terms of retained impact types, the sign and magnitude of the estimated regression coefficients, and the relative importance of the different impact types with respect to the overall impact. The full results of the backward stepwise selection are provided in Table S12 in the Supplementary Information.

3 Results

3.1 Descriptive statistics: socio-demographic variables

The socio-demographic characteristics of the sample, for the different exposed groups, are reported in Table 2 and compared with statistics provided by ISTAT for the municipalities of Senigallia, Ostra and Trecastelli. Out of the 698 respondents, 43.8% declared to have been directly affected by the flood, 40.1% indirectly affected, and 16.0% reported to have not been affected at all.

The distribution of respondents across gender and age categories demonstrates the representativeness of the sample when compared to the population of the study area. In terms of gender, the proportions of male and female respondents are relatively balanced in the overall sample. However, within the not affected group, there is a slightly higher representation of females (56.2%) compared to the study area population (51.6%). Regarding age, biases can be observed across all groups. Respondents aged 40–59 years are overrepresented compared to their share in the study area population (37.2%). For the youngest age group (18–19 years), a direct comparison with the study area population could not be made, as ISTAT data aggregates individuals aged 15–19 years into a single category, and the questionnaire

Table 2 Socio-demographic characteristics of the respondent groups compared with ISTAT data of 2021 census for the municipality of Ostra, Senigallia and Trecastelli

Variables	N. of respondents (%)					Study area population (%)
	Values	Whole sample	Directly affected	Indirectly affected	Not affected	
Gender	Female	346 (49.9)	147 (48.0)	138 (49.3)	63 (56.2)	51.6
	Male	342 (49.0)	156 (51.0)	138 (49.3)	48 (42.9)	48.4
	Nodata	8 (1.1)	3 (1.0)	4 (1.4)	1 (0.9)	–
	Total	698 (100.0)	306 (100.0)	280 (100.0)	112 (100.0)	100.0
Age	18–19 years	13 (1.9)	3 (1.0)	7 (2.5)	3 (2.7)	–
	20–39 years	154 (22.1)	54 (17.6)	79 (28.2)	21 (18.8)	23.4
	40–59 years	335 (48.0)	158 (51.6)	123 (43.9)	54 (48.2)	37.2
	> 59 years	196 (28.1)	91 (29.7)	71 (25.4)	34 (30.4)	39.4
	Total	698 (100.0)	306 (100.0)	280 (100.0)	112 (100.0)	100.0

The numbers in parentheses depict the percentage of respondents within each group

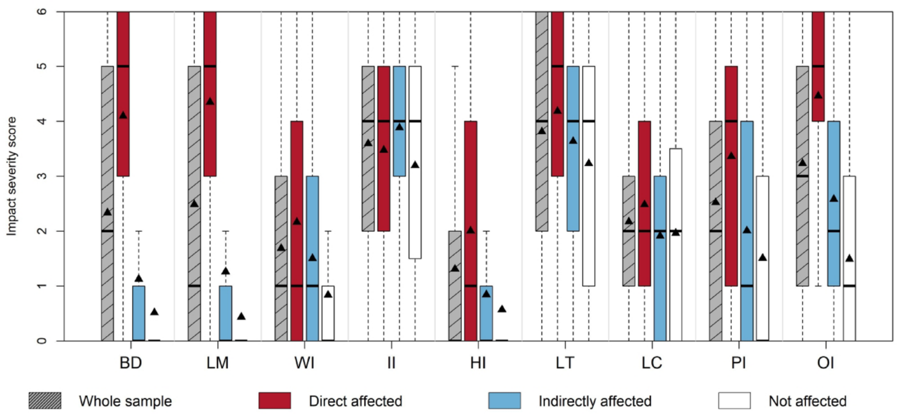

Fig. 4 Boxplots of the perceived severity of impact for the whole sample and the different respondent groups; the triangle depicts the mean values. BD, Building physical damage; LM, Loss of memorabilia; WI, Work interruption; II, Infrastructure inaccessibility; HI, Physical health impacts; LT, Loss of trust in institutions; LC, Loss of community cohesion; PI, Psychological impacts; OI, Overall impact

was restricted to individuals aged 18 and over. Despite the observed biases, the inclusion of all age groups in the sample allowed to drawn conclusion with respect to the RQs.

3.2 Descriptive statistics: perceived severity of impacts

The differences in the perceived severity of flood impacts across the three exposed groups are depicted in Fig. 4. Although a high degree of variability is observed across all impact types and respondent groups, Kruskal–Wallis tests confirmed that perceived impact severity differs significantly across exposure groups for all impact types (all $p < 0.002$, see Table S5 in the Supplementary Information). Regarding the overall impact (OI), pairwise comparisons of mean ranks indicated that all three exposed groups differ significantly from each other (see Table S6 in the Supplementary Information). OI mean values are progressively decreasing with flood exposure, with directly affected individuals reporting a mean value of 4.5 (median = 5), indirectly affected a mean of 2.6 (median = 2) and not affected respondents a mean of 1.5 (median = 1).

Specific scores for individual impact types across the three respondent groups are discussed in the following subsections.

3.2.1 Directly affected respondent group

Among the directly affected respondent group, the most severely perceived impact was the loss of memorabilia (LM), with a high mean value of 4.4 (median = 5). This was followed by the loss of trust in institutions (LT), which also showed a high perceived impact, with a mean value of 4.2 (median = 5). Building damage (BD), which is the most common indicator of flood impacts, was perceived as the third most severe impact, with a mean value of 4.1 (median = 5). Infrastructure inaccessibility (II) and psychological impact (PI) showed mean values of 3.5 (median = 4) and 3.4 (median = 4), respectively. These were followed by loss of community cohesion (LC), with a mean value of 2.5 (median = 2), work interruption (WI) with a mean value of 2.2 (median = 2), and health impact (HI), with the lowest mean value of 2.0 (median = 2). Despite lower mean and median values, these latter impacts show high variability (see Fig. 4), suggesting heterogeneous experiences within the group.

3.2.2 Indirectly affected respondent group

For the indirectly affected respondent group, the highest mean score was recorded for II, with a mean value of 3.9 (median = 4), followed closely by LT with a mean of 3.6 (median = 4). PI exhibits a mean of 2.0 (median = 1), followed by LC with a mean of 1.9 (median = 2), and WI with a mean of 1.5 (median = 1). Both BD and LM presented a mean score of 1.3 (median = 0). The lowest severely perceived impact was HI, which obtained the lowest mean score of 0.8 (median = 0). This low score is due to the fact that only 3.6% of indirectly affected respondents reported experiencing health impacts, i.e., provided non-zero scores (see Table S3 in the Supplementary Information).

3.2.3 Not affected respondent group

For the not affected respondent group, II and LT were the most severely perceived with a mean value of 3.2 (median = 4). These were followed by LC with a mean value of 2 (median = 2), PI with a mean value of 1.5 (median = 0) and WI with a mean value of 0.8 (median = 0). BD, LM, HI present very limited variability (see Fig. 4) with mean values of 0.6, 0.5, and 0.4, respectively (medians = 0). This means that the vast majority of respondents reported zero score for these impacts (see Table S4 in the Supplementary Information). On the other hand, this also means that some respondents did not assign a zero score to direct impacts, contrary to expectations. A possible explanation is that the catastrophic nature of the event influenced the perception of the broader community, leading some respondents to assess the severity of impacts based on what they observed happening to those directly affected, rather than their personal experience.

3.3 Multiple linear regression

As shown in Table S11 in the Supplementary Information, the variable loss of memorabilia (LM) within the not affected group exhibited a tolerance statistic below the threshold of 0.2, indicating potential multicollinearity. Therefore, LM was excluded from the multiple linear regression model for this group. The results of the regression analyses are presented in Table 3.

The following subsections present the order of importance of each impact type across groups and the whole sample, as well as the results obtained from the application of a stepwise selection procedure based on AIC.

3.3.1 Directly affected respondent group

For directly affected respondents, both PI and BD were highly significant ($p<0.001$) in explaining the overall impact perception, with BD exhibiting a higher regression coefficient (β = 0.31) than PI (β = 0.20). LM emerged as the third most significant factor ($p<0.01$) with the third highest regression coefficient (β = 0.12), followed by LT which also showed statistical significance (β = 0.09, $p<0.05$). HI, WI, II, and LC were no significant predictors of OI among directly affected residents. The coefficient of determination (R^2) reached a value of 0.48, meaning that 48% of the variation in OI was explained by the selected impact predictors.

3.3.2 Indirectly affected respondent group

Among indirectly affected respondents, PI was the most significant impact in explaining OI, exhibiting the highest regression coefficient (β = 0.22, $p<0.001$). LM resulted the second strongest predictor (β = 0.21, $p<0.01$). II and LT showed equal coefficient values (β = 0.17) and significance levels ($p<0.01$). Finally, WI was found to be significant ($p<0.05$), with a slightly lower beta coefficient compared to the other impacts (β = 0.15). Surprisingly, HI resulted significant too but with a negative coefficient (β = −0.16, $p<0.05$). BD, and LC were not significant predictors of OI. The model explained 34% of the variance ($R^2=0.34$).

3.3.3 Not affected respondent group

For not affected respondents, significant impacts were identified as well, with PI and WI emerging as the most influential predictors of OI. Although both variables presented the same regression coefficient (β = 0.35), PI showed a higher level of statistical significance than WI ($p<0.001$ for PI and $p<0.01$ for WI). Finally, II also emerged as a significant predictor of OI at the 10% significance level (β = 0.13, $p<0.1$). Consequently, BD, LM, HI, LT and LC did not significantly contribute to the explanation of OI. The model accounted for 40% of the variance ($R^2=0.40$).

3.3.4 Whole sample

Considering the whole sample, seven out of eight predictors were statistically significant, with the only exception being LC. The direct impacts of BD and LM, as well as the indi-

Table 3 Result of regression analysis for the whole sample and the three groups of respondents

	Whole sample			Directly affected			Indirectly affected			Not affected		
	N = 694			N = 305			N = 277			N = 112		
	$R^2 = 0.53$			$R^2 = 0.48$			$R^2 = 0.34$			$R^2 = 0.40$		
	β		SE	β		SE	β		SE	β		SE
Intercept	0.84	***	0.14	1.70	***	0.22	0.51	*	0.25	0.37		0.28
BD	0.23	***	0.04	0.31	***	0.04	0.03		0.07	−0.20		0.15
LM	0.21	***	0.04	0.12	**	0.04	0.21	**	0.06			
WI	0.09	**	0.03	0.02		0.03	0.17	**	0.06	0.35	**	0.10
II	0.07	*	0.03	−0.03		0.04	0.16	**	0.06	0.13		0.07
HI	−0.10	**	0.04	−0.02		0.04	−0.16	*	0.07	0.10		0.16
LT	0.12	***	0.03	0.09	*	0.04	0.17	**	0.06	−0.01		0.09
LC	−0.02		0.04	0.05		0.04	−0.04		0.06	−0.02		0.01
PI	0.26	***	0.03	0.20	***	0.04	0.24	***	0.05	0.35	***	0.09

Significance codes: '***' $p<0.001$; '**' $p<0.01$; '*' $p<0.05$; '.' $p<0.1$; β, Multiple regression coefficient; SE, Standard Error; BD, Building physical damage; LM, Loss of memorabilia; WI, Work interruption; II, Infrastructure inaccessibility; HI, Physical health impacts; LT, Loss of trust in institutions; LC, Loss of community cohesion; PI, Psychological impacts rect impacts of PI and LT, were highly significant ($p<0.001$), with PI showing the highest regression coefficient ($\beta=0.26$), followed by BD (0.23), LM (0.21), and LT (0.12). WI ($\beta=0.09$, $p<0.01$) and II ($\beta=0.07$, $p<0.05$) had smaller but significant positive effects. HI resulted significant too but with a negative coefficient ($\beta=-0.10$, $p<0.01$), observed also among the results of the indirectly affected groups.

3.3.5 Stepwise selection

A backward stepwise selection was applied to the complete multiple regression models for the whole sample and each exposed group, whose results are presented in Table 3. This procedure enabled the reduction of model complexity and to assess the robustness of the complete models results by comparing them with the reduced models. The models obtained through the stepwise selection, are reported in Table S12 in the Supplementary Information. According to these final models, the OI for the whole sample and for the different exposed groups can be expressed by the following equations:

$$OI_{allsample} = 0.84 + 0.26 * PI + 0.23 * BD + 0.21 * LM + 0.11 * LT + 0.09 * WI + 0.07 * II - 0.11HI \quad (2)$$

$$OI_{directlyaffected} = 1.60 + 0.31 * BD + 0.20 * PI + 0.12 * LM + 0.10 * LT \quad (3)$$

$$OI_{indirectlyaffected} = 0.51 + 0.24 * PI + 0.23 * LM + 0.17 * WI + 0.16 * II + 0.16 * LT - 0.16 * HI \quad (4)$$

$$OI_{notaffected} = 0.31 + 0.34 * PI + 0.33 * WI + 0.12 * II \quad (5)$$

where Eq. (2) estimates the OI for the whole sample, Eq. (3) for the directly affected group, Eq. (4) for the indirectly affected group, and Eq. (5) for the not affected group. The independent variables are listed in the equations in descending order according to their levels of significance and the value of their regression coefficients.

Comparing the equations with Table 3, it can be observed that the stepwise selection procedure retained only the predictors resulting significant in the complete models. Although coefficient estimates were not identical, they showed the same sign and remained close in magnitude; the relative importance of impact types remained consistent across the whole sample and exposed groups.

4 Discussion

In the following section, the most relevant impact types highlighted by the descriptive statistics and regression analysis are discussed in detail, answering to RQs 1 to 3; this discussion is enriched by insights from the comments to open-ended questions provided by respondents and contextual information. The implications of the results for flood risk modelling and management are discussed as well.

4.1 Answers to the research questions (RQ1, RQ2, RQ3)

The descriptive statistics allowed to identify which impact types were rated as most severe on average for each group, thus answering to RQ1 and partially to RQ3. Loss of memorabilia (LM), loss of trust in institution (LT) and building damage (BD) were scored as the most severe impacts among the directly affected group, with mean scores exceeding 4; infrastructure inaccessibility (II) and LT were the most severe for the indirectly affected, with mean scores slightly below 4; II and LT resulted the most severe also for the not affected group, although their mean scores were lower (i.e. slightly above 3) compared to those reported by the other two groups.

Across all groups, the high scores for LT were expected as the rapid dynamic of the event prevented timely and effective warnings. This result shows that shortcomings in authorities' emergency management can influence the confidence in institution across the entire community. Similarly, the high scores for II among non flooded groups were expected as well. Considering the systemic nature of infrastructures, their physical damage has influence on a broader area than the one at which the physical damage occurs (Menoni et al. 2016; Arrighi et al. 2021). In contrast, health impacts (HI) were the less recorded among all groups, with high percentage of zero values (i.e., impact not experienced) across non flooded groups (see Tables S3 and S4). For what concern the overall impact (OI), respondents who experienced flooding in their homes reported, on average, higher OI scores than those who did not. Although by definition no overall impact would be expected for the not affected group, Fig. 4 shows that at least half of these respondents reported a non-zero level of perceived severity (see also Table S4), suggesting that the exceptional nature of the event had repercussions on the entire community.

The regression analysis allowed to address RQ2 and complete the response to RQ3. Building damage (BD) resulted to be the most important predictor of the overall flood impact (OI) for the directly affected group. However, OI cannot be solely explained by BD. A linear regression model using BD as the only predictor (not shown here) accounted for only 33% of the variance in OI compared to the 48% explained by the full model (Table 3). Indeed, psychological impact (PI), loss of memorabilia (LM), and lost trust in institution (LT) emerged as further significant predictors of OI. This result highlights the central role of intangible losses even among those who experienced property damage, already demonstrated by previous scholars (Mishra et al. 2022; Penning-Rowsell and Green 2000; Thieken et al. 2016). In line with the extensive literature reporting mental health symptoms arising in those affected by a flood (Di Fiorino 2005; Mason et al. 2010; Stanke et al. 2012; Fernandez et al. 2015; Mulchandani et al. 2020; Golitaleb et al. 2022; Zenker et al. 2024; Bubeck et al. 2025), PI ranked as the second most influential predictor of OI among directly affected respondents.

Among indirectly affected respondents, four out of six significant predictors of OI were indirect impacts (PI, LT, II, WI), as expected, with psychological impact emerging as the strongest predictor. This finding is line with with Carroll et al. (2010) and Peek-Asa et al. (2012) who showed that mental stress and psychological symptoms can be experienced also by those who were indirectly affected by the flood, such as support workers or those who faced work interruption. Surprisingly, the direct impacts of LM and HI emerged as significant predictors of OI. For what concern LM, its significance may be explained by the fact that the indirectly affected group in this study includes also individuals with family members whose homes were flooded. Consequently, respondents may have suffered the loss of items of sentimental value due to the damage to their relatives' homes, as indicated in open-ended comments in the questionnaire. In contrast, the significance of HI is more difficult to interpret due to its negative regression coefficient which contrasts with the physical interpretation of the phenomenon. Further data, also referring to other case studies, are required to fully understand this result.

Finally, for the not affected group, psychological impact (PI) was the most important predictor of OI. This finding further highlights that mental health consequences associated with floods could extend well beyond flooded areas involving the whole community impacted by a flood. As Fothergill et al. (2021) argued, non flooded people may also experience trauma by identifying themselves with those who were directly affected.

Across all groups, PI emerged as a highly significant predictor of OI, while LC showed no statistical significance for any of the groups. This may be attributed to the high mobilization of volunteers in the immediate aftermath of the event, both from across the country and neighbouring areas. The collective response observed in the Marche region aligns with findings from previous studies on flood events, where an increased sense of solidarity and community contributed to the strengthening of social relations in the aftermath of floods (Thieken et al. 2016; Walker-Springett et al. 2017).

4.2 Implications for damage assessment

The findings presented in this study allow a direct comparison between impact types identified as significant in the regression analyses and those currently included in flood damage models. Accordingly, in the following, each significant impact (see Table 3) is discussed separately, examining whether existing flood damage models already address it and, where this is not the case, highlighting current research gaps.

In general, it can be anticipated that there is a clear imbalance between tangible, direct impacts, which are widely modelled, and intangible or indirect impacts, which remain often neglected by current assessment tools (e.g., FEMA 2025).

4.2.1 Building damage (BD)

Among tangible impacts, residential building and contents damage represents the most extensively modelled flood impact in Europe, supported by a large number of established damage functions (Gerl et al. 2016). Nevertheless, these models are still affected by significant sources of uncertainty and should be applied with caution, particularly when transferred across different contexts (Merz et al. 2010; Cammerer et al. 2013; Scorzini and Frank 2017; Molinari et al. 2020). The model comparison presented by (Molinari et al. 2020) shows that models developed in the local context outperform others. Perceived severity of building damage, however, may not scale directly with physical or financial loss alone, as individual characteristics, such as household economic capacity, can shape how this damage is experienced.

4.2.2 Loss of memorabilia (LM)

In disaster mental health research, the loss of memorabilia is considered a relevant stressor contributing to adverse psychological outcomes (e.g., Paul et al. 2014; Gruebner et al. 2016; Tempest et al. 2017). In flood damage assessment studies, loss of memorabilia is understood as an intangible impact, which may be perceived as more severe than tangible damages (Penning-Rowsell and Green 2000; Mishra et al. 2022). While, in this body of literature, loss of memorabilia is qualitatively described as a flood consequence, models explicitly accounting for it are currently lacking. The significance of LM observed in this study, for both directly and indirectly affected groups, highlights the need to move beyond its role as a mere explanatory stressor and to consider it as a distinct impact dimension deserving further investigation and representation in damage assessments, particularly from a long-term health-related perspective.

4.2.3 Work interruption (WI)

Regarding work interruption, models developed in Europe and Italy primarily estimate direct economic damage to business premises (Kreibich et al. 2010; Arrighi et al. 2013; Molinari et al. 2016; Grelot and Richert 2019; Ballocci et al. 2026), without assessing the disruption experienced by workers of affected firms. While some studies provide tools to estimate business interruption duration or shutdown time (Parker et al. 1987; Friedland et al. 2023; Guntu et al. 2026), such approaches are absent in the Italian context. The significance of work interruption (WI) observed in this study, highlights the importance of advancing such modelling frameworks in order to translate direct damage to business into impacts experienced by individuals.

4.2.4 Infrastructure inaccessibility (II)

For infrastructures, a substantial body of literature developed models to assess flood impacts on transport networks, ranging from direct physical damage to functional usability. Beyond physical damage models (e.g., Scawthorn et al. 2006; Kellermann et al. 2016), researchers accounted for road usability during floods (Pregnolato et al. 2017), while others translated transport disruption into loss of accessibility to services, estimating the populations indirectly affected by such disruption (Arrighi et al. 2021; Wassmer et al. 2025). Nevertheless, current approaches often overlook systemic interdependencies between infrastructures, often relying on simplified assumptions or fragmented assessments. For instance, modelling frameworks assessing the propagation of flood impacts from the power grid, a backbone infrastructure, to other systems such as transportation networks remain scarce (Asaridis and Molinari 2023).

4.2.5 Health impacts (HI)

Regarding health impacts, existing modelling approaches primarily focus on flood-related fatalities (e.g., Jonkman et al. 2008; Terti et al. 2019; Alfieri et al. 2020; Yazdani et al. 2023) and human stability in floodwaters, identifying combinations of water depth and velocity that may lead to loss of balance or instability (e.g., Martínez-Gomariz et al. 2016; Arrighi et al. 2017; Lazzarin et al. 2022; Evans et al. 2024). Less attention was devoted to modelling non fatal injuries or infectious diseases, despite these impacts being widely documented in empirical and epidemiological studies (e.g., Alderman et al. 2012; Montalti et al. 2024; Poulakida et al. 2024; Mas-Coma et al. 2025). The significance of health impacts observed in this study beyond direct exposure highlights the need to also capture indirect health consequences of flooding in damage assessments.

4.2.6 Psychological impact (PI)

Empirical studies show that direct flood exposure is consistently associated with increased levels of psychological distress, anxiety, depression, and post-traumatic stress disorder (Mason et al. 2010; Stanke et al. 2012; Fernandez et al. 2015; Golitaleb et al. 2022; Zenker et al. 2024; Bubeck et al. 2025). Although predictive damage models for psychological impacts of flooding are not currently available, several studies identified key predictors of psychological distress. In such studies, mental health outcomes were measured through validated scales and related to demographic and socio-economic characteristics as well as event-related stressors (Paranjothy et al. 2011; Lamond et al. 2015; Graham et al. 2019; Zenker et al. 2024; Bubeck et al. 2025). Nevertheless, findings are inconsistent across the literature, showing contrasting associations with psychological outcomes (Lowe et al. 2013). Further research is therefore needed to consider a broader range of mental health outcomes and explanatory variables, in order to move beyond general observations and support more robust assessments of flood psychological impacts (Crabtree 2012). The findings of this study highlight the need to expand current research to also account for residents of affected communities who were not directly exposed to floodwater.

4.2.7 Loss of trust in institution (LT)

In the disaster risk literature, institutional trust was explored from multiple perspectives, reflecting its central role across the preparedness, response, and recovery phases (for a review, see Bonfanti et al. 2023). However, only a few studies have attempted to investigate trust erosion explicitly as a disaster-related outcome. For example, Lee (2021) combined individual-level survey data with provincial-level disaster statistics to investigate how natural hazards influence various forms of trust in China. Using a multilevel linear model, the study found that both individual exposure and disaster severity were significantly associated with reduced political trust. Socio-demographic factors, income, health status, and social capital indicators were also significant predictors of trust levels. Similarly, Frost et al. (2025) analysed the loss of trust of the 2017 Mexico City earthquake using pre and post disaster survey data. Results showed an average 11% decline in political trust following the event, mitigated by proximity to relief centres. While these studies offer valuable empirical insights, they remain geographically and contextually specific, and do not yet provide generalisable modelling tools. Given the relevance of this impact among non-flooded groups in our study, flood damage modelling efforts are needed to conceptualize and measure LT as an intangible consequence of floods.

4.3 From theory to practice

The classification of impacts by exposed groups presented in this study supports the implementation of effective recovery policies and measures that prioritize the most significant impacts for each group. These findings inform future flood risk management in addressing the needs of not only those directly exposed to floodwaters but also those indirectly affected, both in the pre-event and post-event phases. In the pre-event phase, preparedness strategies should consider flood impacts on the entire community, not just those in high-risk areas and the provision of support system should be designed to integrate all citizens. In the post-event phase, recovery efforts should be more inclusive, ensuring that support extends beyond the flooded area. Such a targeted approach would help to promote an improved well-being for all, as postulated by SDG3.

In particular, the high significance of psychological impact across all the groups in the regression models suggest that future response measures should be better tailored to support all affected groups, including those who did not experience direct flooding but may still suffer psychological consequences. Moreover, open-ended responses in the questionnaire highlight ongoing mental distress nearly two years after the event, underscoring the need for long term psychological support, as in line with previous studies (Zhong et al. 2018; Bubeck et al. 2020).

The loss of trust in institution was significant for both directly and indirectly affected. The findings of this study show then that the loss of institutional trust after an event can extend beyond the flooded area, potentially weakening the collective capacity to prepare for and respond to future floods. In fact, trust in public authorities fosters proactive community engagement encouraging citizens to take necessary precautions and better prepare for disasters (Bonfanti et al. 2023). Therefore, to enhance preparedness for upcoming floods and to strengthen community resilience, it is crucial that responsible authorities rebuild institutional trust by engaging the whole community and by fostering inclusive participation in disaster risk reduction efforts.

Additionally, work interruption and infrastructure inaccessibility resulted a significant impact among non-flooded groups, highlighting the systemic nature of flood impacts on businesses and infrastructure. The discomfort related to these impacts, as well as the loss of income associated with the interruption of work activities, should be addressed by the competent authorities, recognizing that people exposed to flood negative consequences also include those living outside the flooded area.

For the directly affected group, BD emerged as the most significant impact. Given, the secondary effects caused by property damage (e.g., displacement, mental health consequences), it is crucial that timely financial support to affected households is supplied in the recovery phase. At the same time, it is essential to promote pre-event preparedness by encouraging the adoption of property-level adaptation measures.

5 Conclusions and future research directions

This study presents the analysis of data collected through a questionnaire distributed to residents of municipalities affected by the Marche region flood event of 2022. The research aimed to investigate the perception of the severity of flood impacts across the population.

Unlike most of the existing literature, which focus solely on directly exposed populations, three exposed groups were targeted, namely directly affected, indirectly affected and not affected. Directly affected are those who experience direct contact with flood water or whose house has been damaged by the flood; indirectly affected are those experiencing job activity interruptions or with friends or family members impacted by the floods; not affected group is composed by respondents neither directly nor indirectly exposed to the event but living in the study area. This classification allows to capture a wide range of perceived severity of impacts within and beyond the flooded area. Specifically, respondents answered specific questions regarding the perceived severity of eight type of impacts (building damage, loss of memorabilia, health impact, psychological impact, infrastructure inaccessibility, work interruption, loss of trust in institution, loss of community cohesion) and the overall flood impact (OI), with responses ranging from 0 (impact not experienced) to a severity scale from 1 (low severity) to 6 (high severity). Descriptive statistics of perceived severity scores of the impacts were employed to assess, on average, which were the most severe impacts perceived among groups. Multiple linear regression models were applied for each respondent group and the whole sample to assess the role of different impact types in explaining OI.

The findings presented here can contribute to broadening the understanding of indirect and intangible effects of flooding on people. Specifically, this study highlights damage mechanisms experienced by both flooded and non-flooded people that are often overlooked. In doing so, it points out that current estimations of flood impacts on people are insufficient, as assessments typically rely on the number of residents living within the flooded area only. Based on these findings, new research efforts should focus on the development of damage models that account for the significant type of impacts identified, and targeting also indirectly exposed individuals. Nevertheless, it must be acknowledged that the findings presented in this paper are context dependent. It would therefore be desirable for future research to investigate whether similar patterns can be observed and corroborated in other geographical regions and socio-economic settings. Moreover, even though the coefficients of determination achieved by the three complete multiple regression models ($R^2 = 0.48$ for directly affected group, $R^2 = 0.34$ for indirectly affected and $R^2 = 0.40$ for not affected group) indicate that the models effectively capture key determinants of flood impact perception, the predictors used in this study do not fully explain the variance of the outcome variable (OI). This may indicate that additional important factors could be accounted for in the models. To better capture the overall impact, it could be necessary to consider pre-existing individual characteristics, i.e., vulnerability factors present before the flood, that may influence impact perceptions. Future research should thus focus on exploring how individual vulnerabilities influence overall impact perception, with the aim of developing a predictive model.

5.1 Open research

The dataset collected through the questionnaire, whose results are presented in Sect. 3, is provided as Supplementary Material. The dataset includes metadata to facilitate its interpretation. The complete questionnaire, translated from Italian to English, is also included, along with a guide explaining its structure. In addition, the census data on gender and age of the residents of the municipalities of Senigallia, Ostra, and Trecastelli, presented in Table 2 of this manuscript, are provided together with metadata describing their content and the original data sources.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11069-026-08045-5.

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Declarations

Competing interests The authors declare that they have no competing interests.

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