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ORIGINAL PAPER

Cross National study on landslide awareness and risk management

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Abstract
Coastal communities are facing growing landslide risks due to climate change, with variable rainfall patterns exacerbating their vulnerability. Landslides result in significant casualties and economic losses, highlighting the need to better understand community perceptions and responses. This study analyzed landslide preparedness and response in coastal communities of Bangladesh, Portugal, and Taiwan. Open-ended questionnaires were distributed to residents in areas prone to landslides. Data were further analyzed using computational topic modeling to extract core themes and decision tree analysis to predict adaptation behaviors based on influencing factors. Findings reveal distinct vulnerabilities and adaptive capacities in each study site, emphasizing the importance of tailored strategies for disaster risk reduction. Socio-economic variables such as education, employment status, and community shaped perceptions of landslide risk perception and mitigation behaviors. Varying levels of trust between countries had implications for the effectiveness of response strategies. This cross-national comparison advances global efforts to strengthen adaptation and reduce risks in landslide-prone coastal regions. Our findings underscore the need for tailored, community-specific disaster management strategies and highlight the value of integrating socio-demographic factors into risk assessment and mitigation planning.

Keywords Community perception · Decision tree · Natural language processing · Coastal landslides

1 Introduction

Climate change has intensified the frequency and severity of natural hazards, including landslides, which increasingly threaten livelihoods, infrastructure, and ecosystems (Walton et al. 2021; Haque et al. 2019a, b). Coastal areas are particularly vulnerable due to wave erosion, sea-level rise, and human-driven environmental degradation. The United Nations Environment Programme (UNEP) reports that 34% of global coastal zones face high degradation risk, with Europe and Asia most affected (Evelpidou and Spyrou 2024). With over

Extended author information available on the last page of the article

40% of the world's population living near coasts, addressing landslide risk is critical for sustainable development (McGranahan et al. 2007).

Earthquakes, heavy rainfall, deforestation, and unplanned urban expansion often trigger landslides (Haque et al. 2019a, b). While these physical drivers are well-documented, the socio-political dimensions of landslide risk, such as community awareness, trust in government, and the role of local institutions, remain underexplored (Petkova et al. 2015; Ma et al. 2024). Public awareness and education are vital for early warning responses, yet many communities, especially in developing countries, lack access to risk information, evacuation planning, and disaster mitigation resources (Shaw et al. 2004).

The persistent absence of culturally appropriate disaster risk messaging largely stems from a lack of empirical data to inform its design within specific community contexts. Although practitioners acknowledge the value of culturally sensitive communication, this recognition seldom leads to the systematic collection of information on local communication preferences, trusted messengers, linguistic nuances, or cultural beliefs about risk. This evidence gap prevents both the development of truly culturally appropriate messaging and the creation of evaluation frameworks to assess cultural effectiveness (Hemachandra et al. 2020). Addressing this deficit requires intentional investment in formative research exploring the cultural dimensions of risk communication before emergencies occur, ensuring that disaster messaging is grounded in evidence rather than assumption. Only through systematic collection of culturally contextualized data can the field move from recognizing the importance of cultural appropriateness to achieving it in practice. To better understand these gaps, there have been calls for strategies to better incorporate local knowledge, participatory mapping, and culturally appropriate messaging into mainstream disaster policies (Refulio-Coronado et al. 2021; Khadka et al. 2022). Among these, perception-based approaches are recognized to offer valuable insights into Disaster Risk Management (DRM). However, adaptation strategies often fail to align with community perceptions. This disconnect is especially problematic given that current research frequently overlooks the disproportionate impact of landslides on vulnerable populations and rarely incorporates sociodemographic factors or adaptive capacity. As a result, marginalized groups living in high-risk areas face heightened vulnerability due to inadequate recognition of their specific needs and challenges (Fekete 2019; Bukhari et al. 2023). Understanding different community interpretations and responses to landslide risk is, therefore, essential for developing more effective, inclusive, and equitable disaster risk reduction (DRR) strategies.

An additional challenge is that trust in government plays a pivotal role in disaster response (Wachinger et al. 2013). Transparent communication, competent early warning systems, and inclusive governance enhance trust and cooperation (Terpstra 2011). Conversely, delayed responses, inadequate compensation, or inconsistent policy enforcement rapidly erode public trust, especially in vulnerable communities with histories of political marginalization. In regions like South Asia and Latin America, distrust in disaster response mechanisms is prevalent, undermining public compliance with preparedness efforts (Allen 2006; Amin et al. 2014; Haque et al. 2019a, b). Experts assert that knowledge co-production, community hazard mapping, and inclusive decisions build trust and improve landslide response effectiveness (Twigg 2015).

Within the Disaster Risk Reduction (DRR) framework, key challenges arise between the need for locally grounded research and the demand for systematic comparative data. Disaster risk is inherently context-specific, requiring community-based data collection and engagement to reflect local vulnerabilities, capacities, and cultural perceptions of risk. Such approaches recognize that effective DRR interventions must build on lived experiences and indigenous knowledge, as risk is socially constructed and locally manifested. However, the field still lacks comprehensive comparative data across diverse geographic and cultural settings, constraining the identification of transferable strategies and scalable resilience practices. The goal of comparative analysis is not to promote universal solutions but to discern underlying patterns and adaptable principles that inform context-sensitive interventions. Advancing this agenda requires research designs that balance local specificity with cross-context comparability, thereby strengthening both community relevance and the global evidence base for DRR policy and practice. Despite the global rise in landslide impacts (Haque et al. 2016, 2019a, b), research remains largely region-specific, with limited comparative studies across countries that differ in their political, cultural, and socioeconomic contexts.

These persistent challenges—the disconnect between technical hazard assessments and local perceptions of risk, as well as a lack of trust in institutions and disaster communication systems- have weakened landslide preparedness and response efforts, as well as a tendency for landslide risk awareness to be overshadowed by other hazards, such as earthquakes and floods, resulting in limited sustained attention and investment. Moreover, while advanced monitoring techniques have greatly improved scientific understanding, they rarely integrate with socio-behavioral insights, leaving risk management strategies technically sophisticated but socially disconnected. Clarifying and addressing these challenges is essential for developing disaster preparedness approaches that are not only scientifically robust but also socially trusted and culturally relevant.

This study was designed to address these gaps through a cross-country comparative framework that examines landslide risk awareness and preparedness in Bangladesh, Portugal, and Taiwan. These countries represent diverse landscapes, political systems, and disaster management infrastructures, ranging from well-established community-based models to resource-constrained systems. By integrating community-level variables such as disaster mitigation teams, evacuation maps, and public communication strategies with individual-level variables on socio-demographic factors, education, and outreach, the study explored how interactions between individual and community capacities influence preparedness and response.

2 Materials and methods

2.1 Conceptual framework

Understanding community vulnerability, resilience, and adaptive capacity is crucial for sustainable DRM in landslide-prone areas. Various theoretical frameworks analyze community perceptions, preparedness, and responses. This study adopts a multi-level framework, assessing individual, community, and national risks, with an emphasis on local knowledge, socio-economic factors, and cross-regional collaboration to develop effective, context-specific adaptation strategies for coastal landslide resilience (Fig. 1) (Scaioni 2013; Alcántara-Ayala and Moreno 2016; Eidsvig et al. 2017; Mavhura et al. 2017; Mentaschi et al. 2018; Paterson and Charles 2019; Arkhurst et al. 2022; Oven et al. 2022; Ma et al. 2024; Shan et al. 2024).

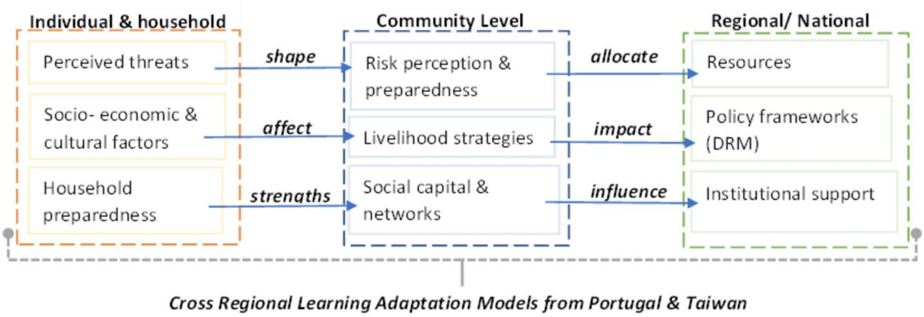

Fig. 1 Conceptual framework to provide successful strategies to inform household preparedness, community resilience, and government policies in Bangladesh

Recent advances in artificial intelligence and deep learning have significantly enhanced landslide detection and susceptibility mapping. For instance, large-scale vision-language models such as SpectralGPT have demonstrated strong cross-domain generalization for geohazard identification using spectral data (Zhou et al. 2024). Similarly, interpretable deep unfolding networks like LRR-Net (Li et al. 2023) integrate sparse representation and deep feature learning to improve hyperspectral anomaly detection with explainable outputs. These AI-driven approaches highlight the potential of data-intensive models to capture complex spatial and spectral dependencies in environmental systems. In contrast, our study emphasizes interpretable and stakeholder-accessible methods, employing Decision Trees and Natural Language Processing to explore socio-behavioral dimensions of landslide risk. This complements data-driven hazard mapping by providing insight into how community perception, awareness, and institutional factors shape real-world disaster preparedness.

2.2 Study areas

Bangladesh, Portugal, and Taiwan were selected for their high landslide susceptibility (Fig. S1) and existing research networks. Each faces unique hazards shaped by geography and climate. Bangladesh's Chittagong Hill Tracts suffer frequent rainfall-induced landslides, worsened by deforestation and unchecked development. Portugal faces challenges from rainfall-triggered landslides, wildfires, and coastal erosion. At the same time, Taiwan's location in the Pacific Ocean, near the convergence zone between the Eurasian and Philippine Plates, and its steep terrain create risks from typhoons and earthquakes (Fig. S1).

The impact varies. Bangladesh's 2021 monsoons caused 170 fatalities (Kamal et al. 2022). Portugal recorded 29 landslides in populous coastal areas (e.g., Algarve in 2009, Madeira in 2010), and Taiwan employed advanced tools, like InSAR, for monitoring its high-risk zones (Haque et al. 2016). From 1995 to 2014, landslides caused 1084 casualties in Bangladesh, 226 in Portugal, and 1854 in Taiwan (Haque et al. 2019a, b).

Bangladesh's disaster framework integrates climate strategies through the Disaster Management Act of 2012 and the Climate Change Action Plan, which is managed by the Ministry of Disaster Management. Efforts include vulnerability mapping, rainfall forecasting, hill-cutting regulations, reforestation, slope stabilization, and community-based early warning systems to protect informal settlements.

As a European Union (EU) member, Portugal mandates mapping flood and landslide risk zones in Municipal Master Plans and major construction projects (Siko 2020). The EU Strategy for Climate Adaptation requires identifying vulnerable areas affected by extreme weather. Risk zones are integrated into the National Ecological Reserve (NER) (Siko 2020), restricting construction. Geotechnical and geological studies are mandatory for large civil and mining engineering projects.

The Portuguese National Disaster Risk Management Plan and Civil Protection System coordinate responses, with regional units developing tailored emergency plans (Shabbir and Pilz 2019). Critical zones may undergo geotechnical monitoring, while national meteorological monitoring issues warn the population of potential hazardous events. Coastal authorities also post warnings in hazardous shoreline areas to ensure public safety.

Taiwan's advanced disaster management system addresses multiple natural hazards through the Disaster Prevention and Protection Act (Vollert 2020). The National Science and Technology Center and the Central Emergency Operation Center provide expertise and coordination (National Science and Technology Center for Disaster Reduction, 2020). Landslide prevention includes the Sediment Disaster Prevention Program, monitoring stations, and early warnings (Gramacy 2020). Measures include mandatory evacuations, emergency shelters, and public awareness campaigns. Standard procedures guide evacuations and recovery, supported by real-time monitoring, hazard maps, and mobile apps. Indigenous knowledge is integrated into strategies, enhancing community resilience in landslide-prone areas.

2.3 Data collation and analysis overview

Data were collected via an online questionnaire targeting landslide-prone hotspots and triggers in Bangladesh, Portugal, and Taiwan (Figs. S1 and S2). Fourteen university graduate students from these countries coordinated the study, each identifying 40 respondents through a snowball sampling approach, while ensuring gender balance and diverse age representation (Table S1). We contacted participants via email and followed up as needed. Non-response rate averaged 32%.

Surveys in Bangladesh and Taiwan were conducted in English, while those in Portugal used Portuguese, which were later translated into English for analysis. Questions covering perceptions, experiences, and causes of landslides were rated on a 1–5 scale (1 = very irrelevant; 2 = irrelevant; 3 = neither relevant nor irrelevant; 4 = relevant; 5 = very relevant). Potential causes indicated included heavy rain, earthquakes, deforestation, slope cutting, and construction. All survey data was handled confidentially.

We used both qualitative and quantitative approaches to analyze the survey data. For open-ended responses, we applied topic modeling, an unsupervised machine learning technique that identifies dominant themes by clustering similar words within a text corpus. This enabled us to detect cross-country patterns and summarize key perceptions. Word clouds were also generated to visually represent frequently used terms in each question.

For structured quantitative responses related to landslide resilience, we performed a multicollinearity analysis to identify highly correlated features (correlation coefficients greater than 0.5). From correlated groups, we retained only the variable most strongly associated with the dependent variable. Using this reduced feature set, we then applied decision tree (DT) modeling to explore relationships between respondents' perceptions (independent variables) and resilience indicators (dependent variable) (Rokach and Maimon 2014). For instance, participants who were aware of emergency response plans tended to perceive the landslide risk as lower. Although decision trees are expected to inherently handle correlated features, removing highly correlated features can improve interpretability and, in some cases, even enhance performance. In fact, multicollinearity can lead to complex and non-intuitive tree structures, potentially affecting its predictive power if the tree randomly selects one feature over another with similar information.

2.4 Analysis 1: topic modelling

Topic modeling, an unsupervised machine learning (ML) technique that identifies similar words within a body of text, was used to analyze open-ended responses from the survey. This approach enabled the identification of patterns across countries and between different respondent groups. Additionally, word clouds were generated for each question to visually highlight the most frequently used terms. Topic modeling was performed using a custom pipeline based on the Latent Dirichlet Allocation (LDA) method, implemented with the Python Gensim Library. The pipeline followed these steps:

(i) Tokenization—All text was converted to lowercase. Words with fewer than four characters, punctuation, and stop words were removed.
(ii) Lemmatization—Tokens (i.e., lowercase words) were lemmatized using the NLTK WordNet toolkit. Using part-of-speech tags, the function applied transformation rules and queried the WordNet database until a lemma was found, or no further transformations were possible. If unsuccessful, the original token was retained as the lemma.
(iii) Stemming—Each lemma is passed through the Snowball stemmer function, which uses the widely known Porter Algorithm (Porter 2001; Willett 2006).
(iv) Bag-of-words (BoW) and term frequency–inverse document frequency (TF–IDF) conversion—The stemmed tokens were transformed into a BoW representation to compute word frequencies. These were then converted into TF-IDF scores to weigh words according to their importance across the corpus. TF-IDF is calculated as follows:

$$idf_i = log\left(\frac{N}{n_i}\right) \tag{1}$$

$$tf_{i,d} = \frac{f_{i,d}}{N_d} \tag{2}$$

$$tfidf_{i,d} = idf_i \times tf_{i,d} \tag{3}$$

Here, idf_i= inverse document frequency (IDF) of the word (stem) *i*. N=total number of stems across all documents. n_i = number of the stem *i*, across all documents. $tf_{i,d}$ = term frequency of stem *i* for document *d*. $f_{i,d}$ = frequency of stem i in document *d*. N_d= number of stems in document *d*. $tfidf_{i,d}$= TF-IDF for stem *i* in document *d*.

A higher inverse document frequency (IDF) value indicates that a word is relatively rare across the entire corpus and thus more informative when it appears in a specific document. In contrast, a higher term frequency (TF) value reflects the importance of a word within a given document. Therefore, a high TF-IDF score suggests that a word is both frequent in the document and uncommon in the corpus, contributing significantly to the document's meaning.

In our case, each stem is converted into its corresponding TF-IDF value. To ensure comparability across responses, all TF-IDF values are normalized within each document so that their sum equals one.

(v) Latent Dirichlet Allocation (LDA)—An LDA model is trained with the TF-IDF corpus to extract latent topics from textual data. LDA requires a predefined number of topics to perform modeling. To determine the optimal number, we evaluated models trained with varying topic counts using the coherence score, a metric that quantifies the semantic similarity among words within a topic (Blei et al. 2003). We specifically used the u_mass coherence score, which is well-suited for unsupervised evaluation, and it is calculated as follows,

$$C_{UMass} = \frac{2}{N \cdot (N-1)} \sum_{i=2}^{N} \sum_{j=1}^{i-1} log \frac{P(w_i, w_j) + \epsilon}{P(w_j)} \tag{4}$$

where N=Number of top words to be taken for calculation. $P(w_j)$ = Probability of word w_j occurring in a document. $P(w_i, w_j)$= The probability of a document containing both the word w_i and w_j.

The topic count yielding the highest coherence score was selected as the final model. Initial tests were conducted on a sample of responses to determine the appropriate number of topics, followed by full-scale modeling on the complete dataset.

(vi) Word cloud generation—Each LDA-generated topic consists of a list of words; each is associated with a weight indicating its relative importance within the topic (Figs. S3–S18). Based on these weights, word clouds were generated to visually represent the key terms associated with each topic. These visualizations support qualitative interpretation and help guide further thematic analysis.

(vii) Questions for topic modeling—From the full set of survey items, we identified six open-ended questions (Table S2) suitable for topic modeling (Fig. S19). One question was excluded due to an insufficient number of responses for meaningful analysis. The remaining five open-ended questions generated rich textual responses that reflected participants' perceptions, behaviors, and experiences related to landslide risks. These questions captured key aspects of community resilience, including preparedness, livelihood impact, feelings of safety, recovery capacity, and food security.

The topic modeling pipeline was successfully applied to the remaining five questions. The open-ended questions were chosen for topic modeling because they generated rich textual responses. They were selected to represent diverse yet interrelated dimensions of how individuals and communities understand and respond to landslides across different socio-economic and cultural contexts. The datasets from Bangladesh, Portugal, and Taiwan were deliberately selected to capture contrasting geographical, socio-economic, and institutional contexts of landslide-prone regions. Bangladesh represents a developing, high-risk environment with frequent rainfall-induced landslides, Portugal reflects a moderate-risk European setting with structured disaster governance, and Taiwan exemplifies a technologically advanced region with frequent typhoon- and earthquake-induced landslides. These countries collectively provide a balanced cross-national sample encompassing diverse vulnerabilities and adaptive capacities.

2.5 Analysis setup 2: predictive models

To explore how perceptions related to landslide resilience vary across respondents, we conducted a decision tree analysis based on a structured survey in order to develop a predictive model that would understand how answers to a set of questions (independent variables) relate to perceptions of safety from landslides (dependent variable). The steps are outlined in Fig. S20.

(i) Data preparation—We manually identified six binary questions (set *S*) related to national resilience to landslides (Table S5). The outcome variable (*q*) was the respondent's perception of safety from landslides. Each "yes" response was encoded as 1, and "no" or missing responses were encoded as 0. Each question in *S* was given a short descriptive label to serve as a feature in the DT model.
(ii) Multicollinearity analysis—We assessed multicollinearity among the features in *S* using Tolerance (TOL) and Variance Inflation Factor (VIF) metrics. Variables were considered not collinear if TOL < 10 or VIF < 0.1. The TOL and VIF values were calculated as follows,

$$R_i{}^2 = 1 - \frac{\sum_i \left(y_i - \sum_{i=1}^{n} (y_i - (mx_i + c))^2\right)^2}{\sum_i (y_i - \underline{y})^2} \tag{5}$$

$$VIF_i = \frac{1}{1 - R^2{}_i} \tag{6}$$

$$TOL_i = \frac{1}{VIF_i} \tag{7}$$

Here, y_i= i^{th} value of the variable to be predicted. m = slope of the line fitted to the data points. c = constant of the line fitting data points. x_i= i^{th} value of the explanatory variable. $\underline{y}$ = is the mean of the observed data. $R^2{}_i$= residual sum of squares. VIF_i= Variance Inflation Factor of i^{th} value. TOL_i= Tolerance of i^{th} value.

(iii) Correlation analysis—Initial DTs for Bangladesh and Taiwan included all variables, which led to complex trees. To reduce complexity, we generated correlation matrices and identified groups of highly correlated variables (|r|>0.5). From each group, we retained the variable with the strongest correlation with the outcome. We repeated the process using combined data from all three countries. The initial DT was again too complex, so a correlation-based simplification was conducted (Fig. 2), with shaded matrix cells indicating the strength of correlation. Variables were filtered as before.

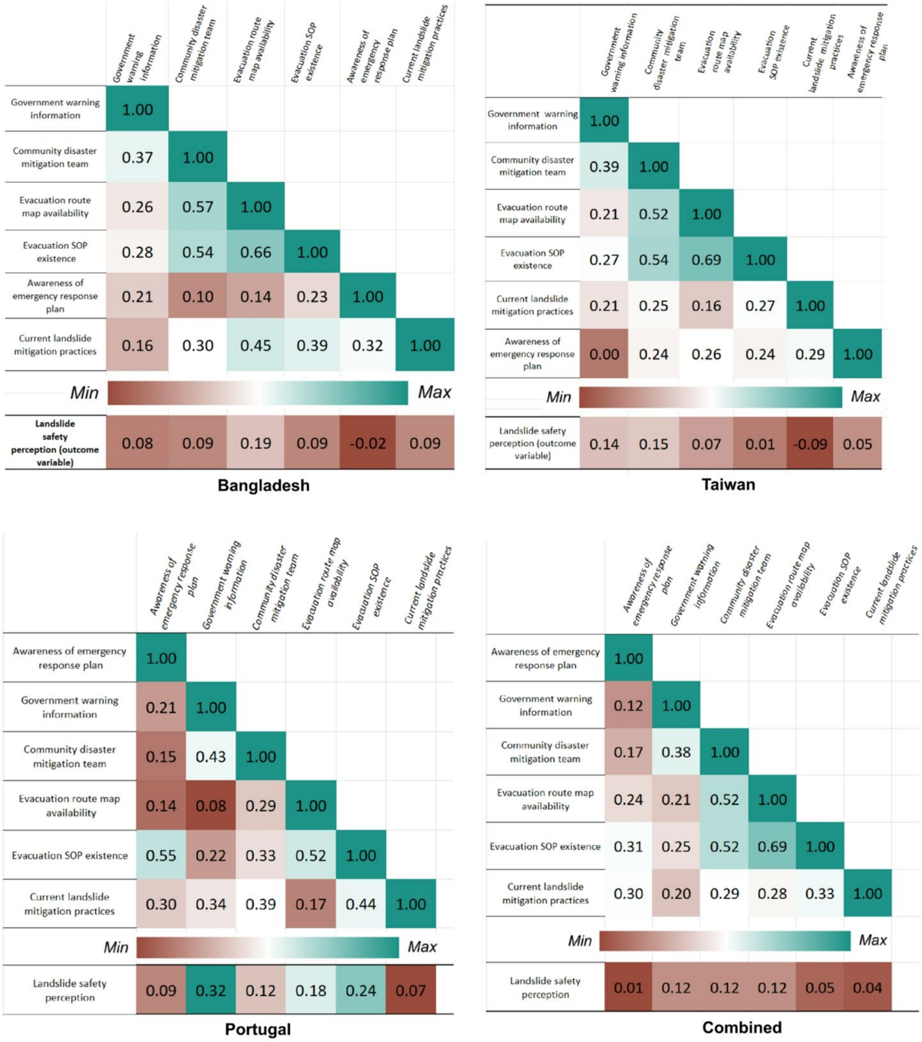

Fig. 2 Correlation heatmap for the features used in the DT for Bangladesh, Taiwan, Portugal, and a combination of them

(iv) Accuracy measure for DT—We used Jackknife cross-validation (leave-one-out) to assess model accuracy (Manly 2005). For each of N data points, the model was trained on N − 1 samples and tested on the remaining one. The average accuracy over all N iterations was used as the final model accuracy. Jackknife accuracy for a predictive model M was calculated as follows,

$$Jack_M = \frac{f_M(1) + f_M(2) + f_M(3) + \cdots\cdots\cdots + f_M(N)}{N} \tag{8}$$

Here, N=Total Number of data Points. $f_M(i)$ = Accuracy when i^{th} data point is used for testing and other *N-1* data point is used for training.

(v) Code, data, and availability—Code and data will be shared upon editorial request and made publicly available after acceptance.

2.6 Sensitivity analysis

We evaluated potential selection bias by dividing the data by sex, education, and age, then calculating the mean response for each subgroup across several outcome variables (e.g., landslide susceptibility due to wildfire or mining). By assigning a weight of 1 to one category (e.g., all college-educated respondents) and 0 to others, we created hypothetical extreme scenarios to assess how each demographic affects results. The goal was to observe how the mean outcome would shift if the survey sample consisted entirely of one demographic group. Comparing these extreme values helped us estimate the potential influence of demographic distribution on the results.

By introducing new samples into a group, the updated mean of an outcome variable for that group would closely approximate the average observed before adding the new samples. This assumption forms the basis for our calculations. From this assumption, we get Eq. 1

$$M_c = \sum_{i=1}^{n} (rg_i \times mcg_i) = \sum_{p=1}^{k} (re_p \times mce_p) = \sum_{j=1}^{l} (ra_j \times mca_j) \tag{9}$$

Here, M_c is the average of an outcome variable *c* (landslide susceptibility for wildfire, etc.). rg_i is the ratio/percentage of a group for a sex category i (e.g. i = 0 for male and i = 1 for females, and so n=2). mcg_i is the average of the outcome variable c for category *i*.

Similarly, re_i is the ratio/percentage of a group for an education level category *p* (*p*=0 for the college-educated group). mce_p is the average of the outcome variable c for category *p*.

ra_j is the ratio/percentage of a group for an age group *j*. mca_j is the average of the outcome variable c for category *j*.

By altering the percentages or weights (rg_i, re_i and ra_j) for sex, education, and age, we can generate new results for sensitivity analysis. This approach enabled us to explore various scenarios, such as what would happen if more individuals with higher education levels were selected, and to assess the impact of each category on the output variable. We have set the weight of one category group to 1 and the others to 0. This presents an extreme case where the entire population comprises only that group. The equation turns into,

$$M_{c\_border\_i} = mcg_i \tag{10}$$

$$M_{c\_border\_p} = mce_i \tag{11}$$

$$M_{c\_border\_j} = mca_i \tag{12}$$

These equations will give different values for each i, p, and j value. The equation indicates that the mean of an outcome variable for a group will be the same as the mean for the total population if the population were composed solely of that group. A simple equation was derived since the outcome variable is the mean (as opposed to the median or other measures). Comparing the border values can give us an idea of how much the outcome variable will fluctuate with changes in different attributes of the population sample. This can also give us an idea about selection bias.

Table S9 lists the 16 specific causes, grouped into five categories. Similar response trends across groups suggest low selection bias, as indicated by overlapping lines in the visualizations. Notably, (a) urbanization factors were widely seen as major causes across countries, and (b) Young Bangladeshis under 18 and grade school-educated individuals viewed rain as less likely to cause landslides.

2.7 Sobol sensitivity analysis

We grouped the 16 outcome variables into natural causes (e.g., rain, earthquakes, wildfire) and human causes (e.g., deforestation, mining, settlements). Animal-related factors were classified as human-driven (Table S10).

Principal Component Analysis (PCA) reduced 16 natural cause variables to PC1, PC2, and PC3, and 7 human cause variables to PC4 and PC5. Using 1,024 randomly sampled responses, we applied Sobol sensitivity analysis based on these PCs.

3 Results

A total of 324 respondents participated in the survey: 159 from Bangladesh (13% non-response rate), 112 from Taiwan (10% non-response rate), and 53 from Portugal (75% non-response rate). 68.52% were male, with 75.93% aged 18–40. Education levels varied, with 48.15% holding postgraduate degrees. The employment status breakdown showed that 42.9% of the population was employed, 41.14% were students, and 12.96% were unemployed. Most respondents lived in households of 3–5 people (65.43%), with similar patterns observed in Bangladesh, Taiwan, and Portugal. Most respondents lived in communities with over 100 residents (62.03%) (Table S1).

Most respondents (65.12%) reported that their dwelling's roofing material was concrete slab (Table S1). Specifically, the rates were 61.01% for Bangladesh, 87.5% for Taiwan, and 30.19% for Portugal. 59.26% mentioned that their floor and outer walls (93.21%) were constructed with cement/concrete. Furthermore, 83.64% of respondents reported living in residential areas (Table S1). Specifically, for Bangladesh, the rate was 74.84%; for Taiwan, it was 90.18%; and for Portugal, it was 96.23%. Respondents reported floods, hurricanes, and landslides in Bangladesh; earthquakes, hurricanes, and floods in Taiwan; and coastal erosion, wildfires, flooding, and landslides in Portugal (Fig. S2).

Figure S2 shows the average relevance assigned to landslide causes by residents in each country. Taiwan exhibits the highest awareness of earthquakes, unstable soil, and prolonged rain (scores near 5), reflecting its seismic activity and public education efforts. Portugal ranks highest for heavy rain (4.5) and unstable soil (4.3), likely due to recent events, with a strong awareness of earthquakes (4.3), as shown in Fig. 3. Bangladesh shows moderate

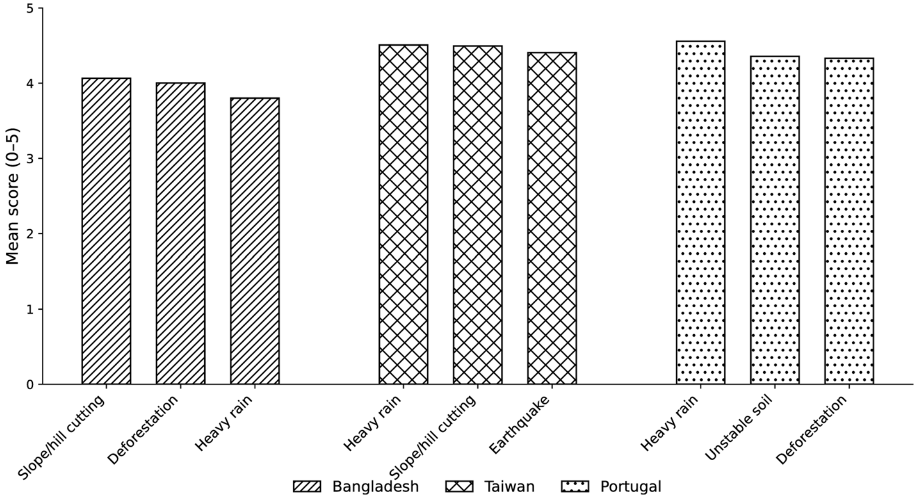

Fig. 3 The top three landslide causes identified in responses for Bangladesh, Taiwan, and Portugal

awareness but lower for heavy rain (3) and traffic/animals (3). Awareness of slope cutting is consistently high (5) across all countries. Taiwan prioritizes environmental risks, such as deforestation (4.5) and settlement increases (4.5), while Portugal emphasizes road deforestation (4.3) and slope/hill cutting (4.3), as shown in Fig. 3. Bangladesh's moderate awareness suggests a need for stronger public education and localized disaster preparedness.

Bangladesh, Portugal, and Taiwan exhibit comparable landslide risk responses, employing proactive measures like higher ground exploration, shelter fortification, and government support. Bangladesh's preparedness and immediate actions are notably lower than those of Portugal and Taiwan, despite a significant increase in awareness and safe evacuation practices. Respondents expressed concern about the insufficient early warning systems, the lack of trained personnel, and the lack of timely information, leading to widespread vulnerability (Fig. 4).

Recovery durations varied across countries due to differing limiting factors. For instance, Bangladesh may face prolonged recovery times primarily due to financial constraints, while other nations encounter different barriers. As the recovery processes are generally resource-intensive, countries with limited economic capacity are also likely to experience delays in responding to future disasters, reinforcing cycles of vulnerability.

When examining perceptions of governmental response, Portugal and Taiwan place more trust in government-coordinated evacuation procedures, relying on military and professional rescue teams, compared to less trust in institutional responses to landslides. Bangladeshi respondents reveal a significant gap in public trust and government efficacy, highlighting the urgent need for improved community-based awareness and disaster management practices (Table S7). Landslide impacts and recovery capacity vary significantly, with Taiwan and Portugal exhibiting better recovery mechanisms than Bangladesh, where economic instability and geological challenges prolong the recovery process.

Fig. 4 Word cloud for responses to questions from Bangladesh, Taiwan, and Portugal

3.1 Decision tree analysis of perceptions of safety

Figure S20 gives a brief overview of generating a decision tree. To generate decision trees, first we conduct multicollinearity analysis. Specifically, we chose the decision tree model because it provides a transparent and easily interpretable structure for identifying relationships between community-level variables (e.g., disaster mitigation teams, evacuation routes, and SOPs) and perceptions of landslide safety. Compared to other machine learning models, decision trees offer visual traceability of decision rules, a key requirement in socio-environmental studies where transparency and stakeholder understanding are crucial.

The results of the study (Table S3) revealed that the maximum Variance Inflation Factor (VIF) value was 2.06 (which is less than the threshold of 10), and the minimum Tolerance (TOL) value was 0.49 (greater than the threshold of 0.1). These findings indicate that there is no multicollinearity issue between the explanatory variables. This suggests that generating decision trees can facilitate the interpretation of data and inform decision-making.

For Bangladesh, as depicted in Fig. 2, the variables 'Community disaster mitigation team,' 'Evacuation route map availability,' and 'Evacuation standard operating procedures—SOP, existence' were highly correlated. Among these three, we chose 'Evacuation route map availability' for DT construction because it had the highest correlation with the outcome variable. We then incorporate other features into the simplified DT construction process, as shown in Tables S4 and S5. Table S6 includes the questions used to create the DT.

For Taiwan, as evident from Fig. 2, 'Community disaster mitigation team,' 'Evacuation route map availability,' and 'Evacuation SOP existence' were highly correlated. Among these three, we chose the 'Community disaster mitigation team' for DT construction because it had the highest correlation with the outcome variable. We then incorporated other features into the DT construction process.

For Portugal, since this DT is neither too large nor too complex, there was no need to conduct the correlation analysis step in this case. The correlation heatmap for the DT for Portugal is given in Fig. 2.

We also constructed a combined DT using data from the three countries' surveys. As evident from Supplementary Fig. 2, the existence of the 'Community disaster mitigation team,' 'Evacuation route map availability,' and 'Evacuation SOP' is highly correlated. Among these three, we chose 'Evacuation route map availability' for a new DT construction because it correlates most with the outcome variable. Additionally, we included other features for DT construction.

Tables S4 and S5 present jackknife accuracy and test accuracy for four decision trees (those for Bangladesh, Taiwan, Portugal, and the Combined DT). The highest accuracy is observed when a combined decision tree is generated for Bangladesh, Taiwan, and Portugal. To assess the performance and efficiency of the Decision Tree (DT) models, we generated Receiver Operating Characteristic (ROC) curves and measured the runtime required for model training and testing. The ROC curves evaluate the model's discriminative ability by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) across different classification thresholds. A higher Area Under the Curve (AUC) indicates stronger predictive performance and better class separation. As shown in Supplementary Fig. S21, the AUC values for the DTs constructed for Bangladesh, Taiwan, and Portugal are over 0.5.

The runtime analysis, also depicted in Fig. S21, reflects the computational efficiency of the models. The runtime per DT generation was under 1.5 s.

Variables such as the presence of a community disaster mitigation team, the availability of evacuation route maps, and the existence of Evacuation SOP consistently exhibited high correlation values. DTs demonstrated high accuracy in predicting resilience-related outcomes, likely due to their ability to capture complex interactions among input variables. However, the results occasionally diverged from intuitive expectations; for instance, higher resilience did not always align with a higher perceived level of safety. This discrepancy suggests that decision tree accuracy might be influenced by contextual factors beyond direct perceptions of resilience. For example, a landslide-prone area may have a well-developed response system, while a less vulnerable region might lack preparedness infrastructure. This highlights the complex relationship between actual resilience and perceived safety, particularly in coastal and hazard-prone regions, underscoring the need for further investigation.

3.2 Results of topic modelling

We analyzed five open-ended survey questions using a topic modeling pipeline, and the resulting word clouds generated by the pipeline for these questions are shown in Figs. 5 and Figs. S3–S18. The combined analysis identified three dominant topics for Question A (Fig. S6): Spreading awareness, shelter, and evacuation. For Question B, the topic model revealed seven dominant themes (Fig. 5): Reduction in production, Traffic interruption, farming is affected, no effect, flooding, affected farming practice, and effect on the community. The word cloud for Question C (Fig. 5) identified three key topics: Living in a safe area, living away from a landslide-prone area, and awareness as a factor contributing to perceived safety.

Similarly, Question D (Fig. 5) revealed three prominent topics: the scale of disaster dependence, financial constraints, and a lack of resources. For Question E, the word cloud (Fig. 5) showed the following dominant topics: Destruction of production, impacts on production, and effects on prices. Collectively, these results offer valuable insights into how respondents perceive safety. Figures S1 and S3–S18 illustrate country-specific landslide causes, topic modeling, community responses, farming impacts, safety concerns, food security implications, factors influencing recovery time, and the application of decision tree analyses.

Landslides primarily impacted agriculture, with effects varying by region. In Bangladesh, participants reported reduced crop yields (Fig. 4), while in Taiwan, the farming community was most affected. Portuguese respondents were less aware of the impacts of farming (Fig. 4). Regarding food security, Bangladeshis noted crop destruction, while Taiwanese respondents linked landslides to rising food prices. In contrast, Portuguese respondents saw no connection between landslides and food production or cost in coastal areas.

Alignment among individual responses often results in fewer topics being identified by the topic modeling algorithm. A lower number of distinct topics suggests greater agreement among respondents, whereas a larger number of topics indicates more diverse perspectives. A high number of topics means the responders vary in their responses. In most cases, the number of topics was three, meaning the responses aligned more closely with real-life situations. The questionnaire also included open-ended questions designed to assess respondents' knowledge and experiences with natural hazards. Responses indicate that many commu-

Fig. 5 Combined Word Cloud of Bangladesh, Taiwan, and Portugal

nities faced landslide risks that were exacerbated by weather-related events. Participants reported significant economic and psychological impacts, including loss of assets and financial hardship. Additionally, several respondents noted that substandard housing construction, often resulting from low socioeconomic status, exacerbates community vulnerability.

3.3 Reliability analysis

In Table S8, we show the results of the reliability analysis. Cronbach's Alpha had a value of 0.751, indicating good reliability. The Kaiser–Meyer–Olkin value was 0.885, demonstrating good sampling adequacy. Bartlett's Test (p-value) is 0.000, which means the null hypothesis can be rejected.

3.4 Sensitivity analysis

As referred, a sensitivity analysis was performed for average susceptibility for causes (Fig. S22) and on 16 outcome variables, grouped into five categories, distinguishing natural and human-induced causes of landslides (Fig. 6). PCA reduced the variables to five principal components (PC1–PC5) for the Sobol analysis (Fig. 6). The results showed minimal selection bias, with the highest first-order sensitivity (Si = 0.2) observed in Bangladesh for PC1 (natural causes), particularly by sex (Tables S9 and S10).

In Bangladesh, respondents under the age of 18 and with only primary education perceived a lower likelihood of natural causes, such as rain, contributing to landslides. Trends indicate that urbanization-related causes are more influential across countries. Sensitivity varied by education level: Bangladesh showed higher sensitivity to human causes, while Portugal was more sensitive to natural causes.

Figure 6 displays first-order sensitivity indices (Si), where higher Si values indicate greater sensitivity to demographic variables. For Bangladesh, education influenced perceptions of human causes more than natural ones. For Portugal, the opposite pattern emerged. In Taiwan, responses showed consistency across sex and age, but small deviations appeared for respondents with a high school education.

Overall, the results suggest limited selection bias (Fig. 6). Differences were more pronounced in perceptions of human versus natural causes, especially in Taiwan (Fig. 6).

In Taiwan, susceptibility patterns by sex or age were consistent, though slight variations were identified among respondents with only a high school education. Overall, the consistency of responses across different demographic groups suggests minimal selection bias, although human-induced causes elicited more varied interpretations than natural ones.

4 Discussion

Here, we synthesize the key insights from our comparative analysis of survey data collected from three distinct coastal regions: Bangladesh, Portugal, and Taiwan, focusing on how individual and household perceptions of evacuation, safety, and recovery are embedded in broader socio-political contexts.

Respondents from all three countries prioritized establishing community disaster mitigation teams, the availability of evacuation route maps, and standard operating procedures for evacuations as fundamental components of their risk management strategies, along with confidence in weather forecasting systems. The coastal regions in the three countries share similar geographical and environmental characteristics relevant to landslide risk, making these measures equally relevant and effective in all areas.

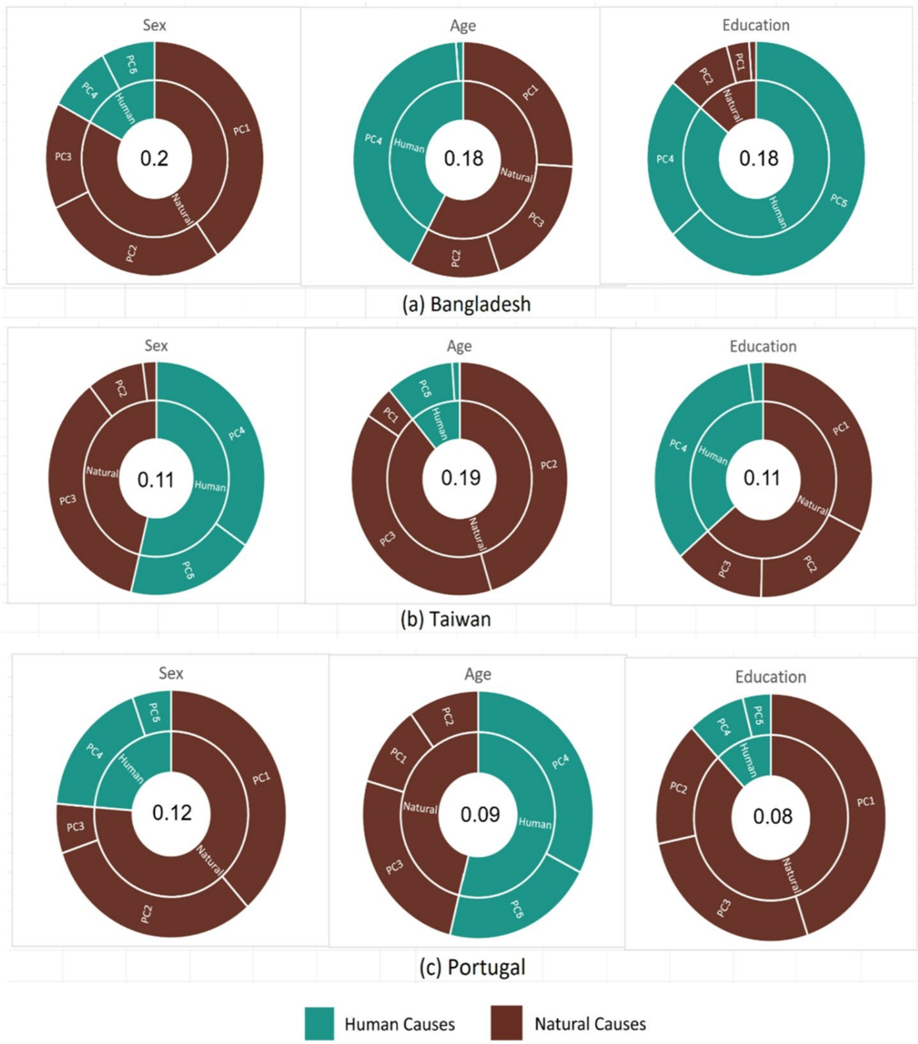

Fig. 6 Sobol sensitivity analysis on the PCA of the outcome variable

On the other hand, we observed that cross-national differences in awareness, perceived safety, and institutional trust can be better understood when situated within the broader cultural, historical, and political contexts of each country. In Bangladesh, a long history of disaster events combined with limited state capacity has created a perception of institutional fragility. Communities often experience delayed or inadequate government interventions, which erode confidence in official early warning systems and foster reliance on informal networks of neighbors and family. These historical patterns, coupled with highly visible socio-economic vulnerabilities, help explain why Bangladeshi respondents report moderate awareness but limited trust in formal disaster communication mechanisms (Uddin et al. 2020; Choudhury and Haque 2024).

In contrast, Portugal's disaster governance is strongly embedded within European Union regulatory frameworks, which mandate risk mapping, municipal preparedness plans, and civil protection systems. This supranational context has promoted both accountability and a culture of compliance, shaping public expectations of government responsibility in hazard management. The country's experiences with catastrophic wildfires in recent years have also sharpened public attention to risk communication, with media frequently framing disasters through the lens of state responsibility and accountability. Consequently, Portuguese respondents express comparatively higher levels of institutional trust, particularly in evacuation procedures and recovery planning (Petersen et al. 2018).

Taiwan presents yet another trajectory. The country's exposure to recurrent typhoons and earthquakes have led to sustained investment in public education and technological preparedness since the devastating 1999 Chi-Chi earthquake. Early warning systems, mobile applications, and well-publicized drills reinforce a culture of responsiveness and normalize preparedness behaviors. The role of the media is equally crucial: disasters are reported in real-time, with government communication strategies emphasizing transparency and scientific evidence. These features contribute to both a higher awareness of landslide triggers and a stronger sense of institutional reliability (Jang et al. 2016; Han et al. 2017; Wei et al. 2019).

The analysis also revealed similarities in the perceived triggers for landslides across three countries, as well as some minor differences. Heavy rain, earthquakes, and unstable soil are the primary natural triggers in all three countries, as well as human activities such as deforestation and slope cutting. Taiwan's increased awareness of natural triggers in landslides (Haque et al. 2019a, b), highlights the effectiveness of its public education programs in a seismic-prone region (Evelpidou and Spyrou 2024).

Taiwanese respondents were highly aware of and prepared for landslides, likely due to the country's robust disaster preparedness and public education initiatives. Portuguese respondents demonstrate a high awareness of heavy rain and wildfires, while Bangladesh respondents exhibit moderate awareness, albeit with lower awareness in specific areas, highlighting the need for increased public education (Petkova et al. 2015; Ma et al. 2024).

Trust in government-coordinated evacuation procedures and disaster response varies significantly among the three countries. Respondents in Portugal and Taiwan exhibit higher levels of trust in government responses, emphasizing the role of effective governance and institutional support in disaster management. In contrast, the responses from Bangladesh reveal a significant gap in public trust and perceived government efficacy, highlighting the need for community-based disaster management practices and enhanced governmental transparency and support.

Landslides impacted farming practices, and food security differs markedly among the coastal regions of each nation, depending on the underlying socioeconomic and cultural context. In Bangladesh, landslides significantly impact crop yields and food security, whereas in Taiwan, the primary concern is the increase in food prices following landslide events. Portuguese respondents, however, report minimal perceived impact on farming and food security, indicating a diverse range of socio-economic vulnerabilities and adaptive capacities (McGranahan et al. 2007; Evelpidou and Spyrou 2024). This may be due to agriculture not being a relevant economic sector in the country.

These findings highlight the role of socio-economic stability and effective disaster management in enhancing resilience to landslides. The respondents' high awareness and preparedness levels in Taiwan and Portugal suggest that economic stability and strong institutional frameworks, which people trust, are basic for effective disaster risk reduction. While the outcomes for Portugal and Taiwan might seem predictable given their socio-economic contexts, the specific strategies and practices observed in these countries offer valuable lessons for improving disaster resilience in Bangladesh, where economic instability and weaker governance frameworks pose significant challenges. For instance, the community-based disaster management models in Portugal and Taiwan could be adapted to the Bangladeshi context to improve public trust and disaster preparedness. Additionally, integrating traditional ecological knowledge with scientific research, as seen in Portugal, can enhance localized disaster resilience and sustainable practices in Bangladesh (Paterson and Charles 2019). By focusing on enhancing public education, strengthening government-community collaboration, and adapting successful models from other nations, Bangladesh can better prepare for and mitigate the impacts of landslides.

Lessons from Portugal and Taiwan's community-based disaster risk management (CBDRM) models are valuable for creating adaptation strategies in Bangladesh. Some key elements that could be introduced could be: (1) Early Warning Systems (EWS)—Taiwan's sophisticated landslide monitoring use remote sensing and AI-based warning could significantly improve Bangladesh's disaster management system; (2) Community Training & Volunteer Networks—Portugal's local response units could be adapted to Bangladesh's informal settlements; (3) Decentralized Governance—Granting leeway to local governments to deploy localized risk amelioration methods, as was done in Taiwan, could enhance voice-data echelons in the international response. Yet adaptation will succeed if challenges, ranging from resource constraints and governance limits to socio-political dynamics, are overcome.

The main limitation of these results stems from the survey being conducted online, which biases the sampling of participants who respond—it primarily represents a more educated and economically stable population. The study faced other sampling limitations, particularly in Portugal, where online surveys were not widely used. Several factors played a role: (1) Survey fatigue—respondents were less motivated to engage with academic research. (2) Availability of digital means—older populations and rural communities were less reachable. (3) Language barriers—though the survey was translated into Portuguese, technical terms may have dissuaded participation. (4) Concerns over data privacy—trust issues probably prevented people from participating. We acknowledge these limitations and strive to reduce bias, complementing our findings with secondary data to provide contextual interpretation and enhance the study's validity.

Demographic skew and a notably high non-response rate in Portugal may affect the representativeness and generalizability to some extent. The respondents in Portugal were mostly highly educated, so perceptions from less educated populations were underrepresented. Nevertheless, since the respondents are older and more educated, it can be assumed that their perceptions may be accurate. A higher non-response rate makes the perception less generalized. But from the sensitivity analysis, it can be seen that the perceptions among respondents align, indicating the effectiveness of the methods. Examining sensitivity analysis, which reveals that human causes are more sensitive (in Bangladesh, based on education), risk communication and land-use training programs tailored to education levels can enhance mitigation uptake. In settings where natural-cause PCs are more sensitive to education (Portugal), prioritizing community awareness and infrastructure measures that address natural hazard exposure can be a prudent step, while also attempting to account for human causes.

Looking ahead, future work could build on this study in several important ways. First, expanding the geographic scope to include additional landslide-prone countries, particularly those with contrasting political or socio-economic contexts, would enhance the comparative framework and allow for more generalizable insights. Second, employing longitudinal designs could capture how awareness, perceptions, and trust evolve over time, especially in response to major disaster events or policy changes. Third, integrating technical hazard modeling and monitoring tools, such as InSAR-based displacement tracking or deep learning susceptibility mapping, into perception-based studies would help bridge the gap between community perspectives and scientific assessments.

5 Conclusion

Community perceptions of landslides were similar across three distinct coastal regions, located in Bangladesh, Portugal, and Taiwan. Raising awareness, implementing warning systems, and fostering collaboration were essential to managing landslide risks effectively for our sample. This requires context-specific adaptation measures that identify commonalities and differences in awareness and preparedness across countries. Insights from this research can help policymakers, planners, and community leaders mitigate impacts and enhance resilience in vulnerable populations. Understanding the socio-economic and political factors that shape risk perceptions is crucial for developing targeted adaptation strategies. The study's comparative design strengthens its findings by highlighting effective approaches to improving landslide resilience. However, its focus on coastal regions may not fully capture landslide risks in inland areas. Further research is needed to explore these aspects and provide a more comprehensive understanding of landslide preparedness and resilience across diverse geographical contexts.

In Bangladesh, strengthening community-based disaster mitigation teams, improving trust through transparent and timely risk communication, and incorporating local ecological knowledge into formal planning are essential for addressing institutional gaps. In Portugal, where regulatory frameworks are already well-established, sustained attention to landslide awareness, beyond the more prominent wildfire hazards, together with participatory mapping at the municipal level, would ensure broader community engagement. Taiwan's advanced technological early warning systems and monitoring infrastructure could be further enhanced by tailoring communication to vulnerable groups and integrating indigenous knowledge into preparedness initiatives. These differentiated recommendations acknowledge the varying institutional capacities and cultural contexts of each country, providing actionable pathways to enhance landslide resilience while reinforcing the comparative insights of this study.

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Author contributions Sabab Aosaf, Safiyeh Tayebi, Ubydul Haque, and M. Sohel Rahman conceived the study design and collected data. Sabab Aosaf and Moeen Hamid Bukhari analyzed data. Sabab Aosaf and Safiyeh Tayebi drafted the initial version of the manuscript. Paula F. Silva & Jian-Hong Wu also contributed to the data collation. Paula F da Silva, Ala Uddin, Gwenyth O Lee, Saleh Ahmed, Atiqur Rahman, Ana Lorena Ruano, and Jian-Hong Wu contributed to the writing and review. Ubydul Haque made the final revisions. All authors read and approved the final version of the manuscript.

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Data availability The data supporting the conclusions of this manuscript are included within the article and can be made available by the corresponding author upon request.

Code availability After acceptance, all custom simulation and analysis codes used to produce the results will be made publicly available in Zenodo, accompanied by a DOI and a reference number. We will provide these details as soon as they become available.

Declarations

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. The research was conducted without commercial or financial relationships that could be construed as a potential conflict of interest.

Ethical approval This study was reviewed by the University of North Texas Institutional Review Board and classified as exempt from IRB review under federal regulations 45 CFR 46.104(d) and 45 CFR 46.117(c)(1)(ii). All participants were over 18 years old, the research complied with applicable guidelines and regulations, and informed consent was obtained from all participants.

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