




# Employing social vulnerability index to assess household social vulnerability of natural hazards: an evidence from southwest coastal Bangladesh

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## Abstract

Vulnerability to hazards not only relies on the extent of natural hazards but also depends on the social and economic conditions of the communities. Therefore, this study intends to construct a household-level social vulnerability at the microscale in the nine wards of Chalna Municipality (CM), Dacope upazila, in southwest coastal Bangladesh by employing the social vulnerability index (SoVI). We surveyed 30 households from each ward to collect data on 33 vulnerability indicators. Of these, seven indicators were extracted by principal component analysis (PCA), which explained 96.34% of the total variance. The PCA results indicate that high population density, poor economic condition, the presence of vulnerable groups, unstable income generating sources, unplanned urban and poor infrastructure, lack of services, and lack of adequate sewage systems are the key drivers of social vulnerability of the CM. The SoVI score was generated using seven PCA outcomes for the respective wards. Results revealed that 44.45% of the areas are medium–high to high (wards 2, 4, 5, and 6) vulnerable. The highest level of social vulnerability was distributed in ward 5, while ward 8 was identified as the least vulnerable. About 33.33% of the CM was found as medium vulnerable areas (wards 1, 7, and 9). Ward 3 was categorized as a low–medium vulnerable area. The findings of the study will provide useful information for decision-makers and disaster managers to develop sustainable disaster management plans for coastal Bangladesh to reduce social vulnerability as well as to decrease the impacts of natural disasters.

**Keywords** Social vulnerability index · Principal component analysis · Chalna Municipality · Social vulnerability · Coastal Bangladesh

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## 1 Introduction

Globally, frequency, as well as the intensity of natural hazards, has been increased over the past decades (Huggel et al. 2015; Aksha et al. 2019; Islam et al. 2017, 2020). This has consequently accelerated the interaction between humans and the environment that makes the people and assets exposed to the hazards, making the community more exposure to vulnerability. The concept of vulnerability was first developed by social scientists, and in the 1970s, it was recognized as a tool to know people's risk perceptions about any disaster (Wisner et al. 2004; Schneiderbauer and Ehrlich 2004; Birkmann 2006). However, the vulnerability of the communities and people in the context of natural hazards does not only rely on the people's closeness to the potential risk, but it also originates from their social vulnerability (SV) conditions (Yoon 2012; Juran and Trivedi 2015). Understanding the SV can provide a possible explanation of why a similar hazard can impact a specific community differently (Morrow 2008). Very few holistic studies exist in the literature on how social differences within their communities can influence the effect of hazards in recent decades, and the SV has gained more and more attention in academic studies. In that sense, the significance of computing the social measurement of vulnerability lies in the circumstance that it permits for the documentation and demarcation of the most hazard-prone regions along with main factors that can contribute to enhancing the resilience of the corresponding communities (Blaikie et al. 2014; Torok 2017).

Scientist emphasizes shifting the SV from the general environment-related vulnerability (Chen et al. 2013). The SV results from the inequality among different groups of people and different places responsible for social stratification. Therefore, understanding the background of people's socioeconomic and political situations along with the knowledge of the underlying factors that increase vulnerability is essential for managing and decreasing SV (Chen et al. 2013).

Most of the coastal communities of developing countries like Bangladesh are vulnerable to multiple shocks and stressors of several disasters due to their extreme poverty and excess dependency on natural wealth (Ribot 2009). Bangladesh is the globe's most vulnerable countries to natural hazards because of its proximity to the sea, geographical location, high population density, lack of awareness, and poor economic status (Rahman and Islam 2019). Wright (2019) stated that people who live in the coastal region and maintain poor livelihood are more vulnerable to the impacts of climate change-induced natural hazards. The southwest coastal region of Bangladesh is mostly affected by tropical cyclones, storm surges, floods, tidal surges, tidal floods, riverbank erosion, salinity intrusion, and sea-level rise (Kibria 2011; Islam et al. 2014; Alam et al. 2018;). The coastal region of Bangladesh has been hit by 159 cyclones, which are tropical depressions, cyclonic storms, and severe cyclonic storms by its nature since 1877–2009 (Sultana and Mallick 2015). Cyclone Aila is severe in its category hit the coastal area of Bangladesh on May 25, 2009, and killed immediately 190 people, and about 3 million people lost their houses and crops (Mallik et al. 2011). The super cyclone Sidr (2007) caused 3406 deaths and vast damages of property (Paul 2009). Several socio-demographic factors such as age, gender, education, income, housing pattern, sanitation facilities, and savings act as the regulating forces to increase the susceptibility of vulnerability to the impacts of natural hazards (Chen et al. 2013). Social vulnerability is a multidimensional construct that measures the sensitivity of a population and its ability to respond and recover from the impact of natural hazards (Cutter and Finch 2008). For effective natural hazard mitigation and implementation process, it is important to quantify the multifaceted nature of SV, especially in the context of disaster

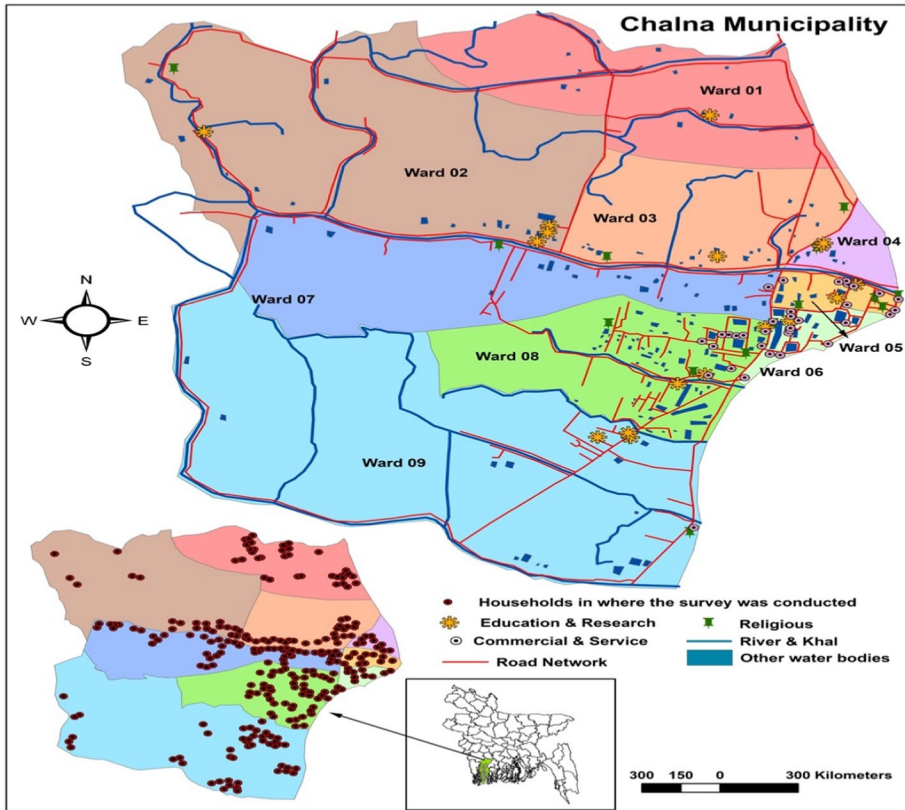
risk reduction strategies (Cutter et al. 2003; Armas 2008; Mendes 2009). Therefore, the SV assessment is essential to reduce losses from disaster and to promote a disaster-resilient community (Cutter 2008).

In recent decades, social vulnerability index (SoVI) developed by Cutter et al. (2003) has been widely applied in various parts of the world such as Asia (Zhou et al. 2014; Gautam 2017), the Caribbean Islands (Boruff and Cutter 2007), Europe (Holand and Lujala 2013; Torok 2017), Africa (Letsie and Grab 2015; Apotsos 2019), and Latin America (Hummell et al. 2016) for assessing SV and recognized as a robust index in the context of assessing SV. For instance, Le Roux et al. (2015) constructed a SoVI in the South African context employing 14 indicators and identified hot spots of SV over South Africa. Torok (2017) developed a SoVI to quantify the SV of Romanian settlements considering natural hazards and argued that high levels of vulnerability linked with low levels of resilience observed in peripheral rural regions, which are frequently affected by natural hazards. Furthermore, Aksha et al. (2019) applied a SoVI in the local context of Nepalese communities and found that a lower level of caste and people unable to speak the language of majority stops access to information and available resources needed for disaster resilience. Apotsos (2019) estimated the spatial pattern of relative SV in urban South African municipalities. However, one of the major drawbacks in these earlier studies is the absence of an objective measurement of the SV. In Bangladesh, few works have been conducted to assess the SV of natural hazards. For instance, Ahsan and Warner (2014) constructed a socioeconomic vulnerability index (SeVI) at the union level using 27 indicators from the 2011 census dataset for climate-affected communities in the southwestern region of Bangladesh. They identified southern and southeastern areas that were more vulnerable than other areas. Rabby et al. (2019) developed a social vulnerability index (SoVI) to determine the vulnerability of communities at the union level in the coastal region of Bangladesh. However, there is no example of the SV assessment at the village or ward level and their driving factors responsible for vulnerability in the past literature. To the best of authors' knowledge, no prior studies in coastal areas of Bangladesh have developed a SoVI at the ward level and did not consider the driving factors for the SV. Nevertheless, the household ward-level vulnerability at the microscale in the coastal communities of Bangladesh is less understood in the existing literature. This study fills these aforementioned research gaps and solving these issues for selecting nine wards of Chalna Municipality (CM), Dacope upazila, in the southwest Bangladesh as a case study area: (1) to develop an aggregated social vulnerability index at household ward level based on 33 SV indicators, (2) to identify the underlying factors and driver of SV, and (3) to analyze the spatial distribution of household-level vulnerability in the CM. The outcomes of this study will help the practitioners and policymakers to devise appropriate rules and take proper initiatives for reducing the social vulnerability, which would then help the respective communities to make themselves disaster resilient.

## 2 Data and methods

### 2.1 Study area

This study was conducted in the CM (lower unit of local government) of Dacope upazila (sub-district), Khulna district, a highly vulnerable region of Bangladesh to tropical cyclones which mostly originated from the southern part of the Bay of Bengal (Fig. 1). Dacope upazila comprises a total of 991.6 km<sup>2</sup> and is divided into ten unions (smaller



**Fig. 1** The location map showing the land use pattern and wards names of the Chalna Municipality (CM), Khulna district, Bangladesh

administrative units) and 26 mauzas. The mangrove forest protects the upazila from the impacts of disasters that are oriented from the Bay of Bengal. The high concentration of canals as well as rivers makes this area more vulnerable to the impacts of floods and erosion. Chalna Municipality is placed between  $22^{\circ}40'$  and  $22^{\circ}35'$  N and  $89^{\circ}25'$  and  $89^{\circ}30'$  E (BBS, 2014) which have nine wards (smallest unit of local government in Bangladesh) (Fig. 1). The municipality covers an area of  $9.49 \text{ km}^2$  with a total population of 14,188. It consists of nine wards and 15 mahalas. The total number of households is 3449. The literacy rate of the municipality is 64.5% (BBS 2018). People of this area maintain their livelihoods mainly by shrimp culture and fishing. Agricultural activities, crab culture, day labor, and honey and wood collection from Sundarbans are further sources of their income. The average land elevation of the municipality ranges between 0.64 and 3.19 m. It stands on the right bank of Pasur and Chunkuri River on the east which flows in a south direction and finally discharges into the Bay of Bengal. The mean annual rainfall is about 2671 mm, with 74% of rainfall occurring during monsoon season (June–September) (Hossain et al. 2014). The area is characterized by tropical monsoon climate (hot and humid weather with abundant rainfall and seasonal variations) with average air temperature ranging from 15 to  $20^{\circ}\text{C}$  in winter and  $30\text{--}34^{\circ}\text{C}$  in the dry summer period. In the southern fringe, the area occupies the world's largest mangrove forest, Sundarbans, which supports the livelihood of

about 3.5 million coastal people. In terms of geographic location and settings, the region is extremely vulnerable to different climate-induced natural disasters such as tropical cyclones, storm surges, floods, tidal surges, tidal floods, riverbank erosion, salinity intrusion, and sea-level rise (Alam et al. 2018). Geographically, the area is noticeably suffering from the brunt of tropical cyclones. The area was extensively damaged by Cyclone Sidr and Aila during 2007 and 2009, respectively (UN 2010).

## 2.2 Data collection

A semi-structured questionnaire survey was conducted in each of the nine wards of the CM. Qualitative along with quantitative techniques were applied for data collection. We considered two data sources: (i) household interviews and (ii) census reports. Before the questionnaire design, a pretesting survey was conducted. Then, the developed questionnaire was finalized after expert consultations. The questionnaire has seven sections: (1) demographic information, (2) social status, (3) economic conditions, (4) natural disaster vulnerability, (5) water use information, (6) sanitation-related information, and finally (7) healthcare facilities.

To choose the size of the sample at an accumulated level, a probabilistic sampling tool was employed to compute the sample size. Kothari (2008) sampling method was employed to define the sample size. We used the confidence interval ( $Z$ ) at 95%, and an error value ( $e$ ) at  $\pm 5\%$ , provided the sample size of 232 households and 26 samples in each ward. We rounded up the total number where 30 households in each ward were surveyed. Approximately, 40 min was allocated to complete each questionnaire. Every tenth household starting from any side of the ward was interviewed. If any household denied taking part in the interview, data collectors preceded to the next household. The only household head was interviewed as they were mainly responsible for earning and maintaining assets. Thus, from nine wards of the studied municipality, we selected 270 households. The survey was conducted from January to February 2019 where the simple random sampling method was used. All secondary data were collected from the 2011 census data. It is worth mentioning that the Bangladesh Bureau of Statistics (BBS) 2011 report is the latest government-authorized census data for collecting demographic data. Still, now, there are no updated census data in Bangladesh. Thus, data on population density, percentage of females, and the number of health facilities were obtained from the 2011 census report.

## 2.3 Variables and indicator selection

Prior studies (Cutter et al. 2003; Boruff and Cutter 2007; Dunno 2011; Letsie 2015; Frigerio et al. 2018; Mavhura 2019) stated that the SV is highly influenced by several components as households' age, gender, education, income, occupation, savings, sanitation facilities, and population density. This study uses the data of people's socioeconomic conditions along with the status of their built environment for developing methods. Initially, 33 variables were calculated from the household survey and census data that are listed in Table 1. Information on percent of female (PFEM), population density (POPEN), and number of health institutions (NHEALTH) is a significant part of developing a quantitative social vulnerability index for the study area. Nonetheless, data on such factors could not be obtained on the household scale. For that reason, we collected data on the household ward level of these factors, which is only accessible in the census report. The race and ethnicity indicators were not used in this study due to data unavailability. This study used an income

**Table 1** Description of the variables used in developing the social vulnerability index for Chalna Municipality

Concept No.	No.	Variable name	Variables description	Data source
Socioeconomic status	1	PINCOME	Percent household income less than 1000\$	Survey
	2	AVGLAND	Average land (ha) per household	Survey
	3	PNOSAVING	Percentage of households having no saving for last one year	Survey
	4	PMORFAM	Percent households more than one family	Survey
	5	PRADIO	Percent households of having radio	Survey
	6	PMOBILE	Percent households of having mobile	Survey
	7	PTV	Percent households of having television	Survey
Gender	8	PFEMWC	Percent female involved in water collection	Survey
	9	PFEM	Percent of female	Census data
Age	10	PFEMLF	Percent female involved in labor forces	Survey
	11	PAGE65+	Percent households of 65 + people	Survey
	12	PAGE5	Percent households of child under 5	Survey
	13	MEDAGE	Median age	Survey
Employed loss (single factor reliance)	14	PAGRI	Percent employed in agriculture/fisheries/forestry	Survey
	15	PLABOR	Percent of employed in day labor	Survey
	16	PBUSINESS	Percent of employed in small business	Survey
	17	PSERVICES	Percent employed in services	Survey
Urban/rural	18	PFUEL	Percent of use of fuelwood as cooking material	Survey
	19	POPDEN	Population density	Census data
Renters	20	PRENTER	Percentage of population living in rented households	Survey
Level of employment	21	PUNEMPLOYED	Percent unemployed	Survey
	22	AVGHH	Average number of people per household	Survey
Family structure	23	PFEMHH	Percent female household head	Survey
	24	PILLIT	Percent of illiterate population	Survey
Education	25	PNOCOLLEGE	Percent of population that not completed college degree	Survey

**Table 1** (continued)

Concept No.	No.	Variable name	Variables description	Data source
Medical services and access	26	NHEALTH	Number of health institutes	Census data
Special need population	27	PDISABLE	Percent population with disability	Survey
Built environment	28	PNOEMBANKMENT	Percent of population living outside embankment	Survey
	29	PNOWATER	Percent households of having no water infrastructure system	Survey
	30	PLOWALL	Percent households of having house with poor external wall	Survey
	31	PNOELECTRICITY	Percent households of having no electricity	Survey
	32	NCYCLONESHELTER	Number of cyclone shelter	Survey
	33	PNOSEWER	Percent households without sewage system	Survey

of less than \$1000 per household as a variable. Variables like “peoples having no saving for the last year” and “living with more than one family” are used as a socioeconomic concept. Unplanned urbanization was another variable. The occupation used as a variable varies from professional workers, day labor, and farmer.

The indicator like “quality of the built environment” is related to the availability of water infrastructure, sewerage system, quality of housing material, living within embankment, and the presence of cyclone shelter. The indicator “lack of water infrastructure (QNOWATER)” represents that household has not the source of running water through supply water or tube well in their home. The households that have no water infrastructure such as shallow or deep tube well and pipe water supply are highly vulnerable. These households would be greatly affected during a natural disaster, especially cyclones, floods, and droughts. The indicator “QNOSEWER” represents the households that did not have a pit or ring slab but did have a hanging latrine. These could be a source of great risk of soil and water contamination after a natural disaster. The households that live outside the embankment (civil engineering structures that are used as dikes for flood control along riverbanks) (Hall et al. 2012) and far away from cyclone shelters are highly vulnerable to natural disasters. The indicator “PLOWALL” is used in this study as households having a house made with low-quality materials such as mud, bamboo, straw, and leaves. It was not easy to discover the variables, which equaled the “medical services and access.” However, this study used the presence of health-related institutions in each ward as an indicator.

## 2.4 Social vulnerability index (SoVI) calculation

Several indexes are developed by experts for assessing the vulnerability, e.g., composite vulnerability index (CVI) (Wells 1997), commonwealth vulnerability index (CwVI) (Atkins et al. 2000), social vulnerability index (SoVI) (Cutter et al. 2003), socioeconomic vulnerability index (SeVI), built environment vulnerability index (BeVI) (Holand et al. 2011), and so on. Among these, the social vulnerability index (SoVI) developed by Cutter et al. (2003) has been widely used and reliable tools to assess vulnerability. Considering some drawbacks, the SoVI framework has gained wide acceptance and popularity because it uses publicly available census data and uses publicly available construction methods and it has easy interpretation of complex social vulnerability concepts (Spielman et al. 2020).

In this study, SoVI was made of 33 variables. Before conducting statistical analysis, all the social vulnerability variables were standardized into *z*-scores. Principal component analysis (PCA) was employed to develop a composite index. PCA is a multivariate statistical technique that is used to reduce a large number of variables into a small number of factors (Każmierczak and Cavan 2011; Bodrud-Doza et al. 2016; Islam et al. 2018). This analysis eases the explanation of component groups and examines the components over time whether any change occurs in total vulnerability. Since all 33 variables were distributed across the nine wards of the CM, the PCA perfectly worked for this study. During analysis, some individual components were produced by PCA which represented all the initial components jointly. Then, the extracted components found by PCA were used for calculating a SoVI for each ward in CM. Using the ArcGIS 10.5 software, SoVI scores were mapped to understand the spatial pattern of SV within the study area.

The Statistical Package for Social Science (SPSS, v.21) was used for performing PCA. Principal components were extracted using the Kaiser criterion, and the components were kept which produced an eigenvalue greater than 1. Varimax rotation was used for ease of interpreting the components and to produce more independent factors. It also helps to



minimize the number of highly loaded variables into a single factor, thus increasing the percentage variation between each of the factors (Armas and Gavris 2013; Islam et al. 2018). This approach was carried out repeatedly until stable and statistically robust components were found. Kaiser–Meyer–Olkin (KMO) of sampling adequacy and Bartlett’s test of sphericity were used to check the robustness of the model. Using the results of PCA, variables with maximum loadings within components were extracted from the rotated component matrix to realize the denotation of produced independent components. Each component was assigned name and cardinality. The components that increase vulnerability were attributed to positive signs, and those reduce vulnerability were attributed to the negative sign. An absolute value was assigned for those components which had the likelihood of positive in addition to a negative indication of SV. A composite SoVI score was calculated for each ward by adding the score of each component. An additive model was used for adding the individual score of all components. In the absence of any theoretical justification of the weighting of the components, the additive approach seemed to be the most practical (Hummel et al. 2016; Cutter et al. 2003). The total SoVI for the CM was calculated for each ward (nine wards) by adding the value of the principal component:

$$\text{SoVI} = \text{PC1} + \text{PC2} + \text{PC3} - \text{PC4} + \text{PC5} + \text{PC6} + \text{PC7} \quad (1)$$

The following flowchart is adopted for this study (Fig. 2).

## 2.5 Ethical consideration

The permission of respondents was taken before the questionnaire survey, and they keep on anonymous. All the respondents were informed about the specific purpose of this work before arranging to the questionnaire. Anonymity and confidentiality of the datasets were confirmed. The formal ethical consent of this work was taken from the respective disaster management authority.

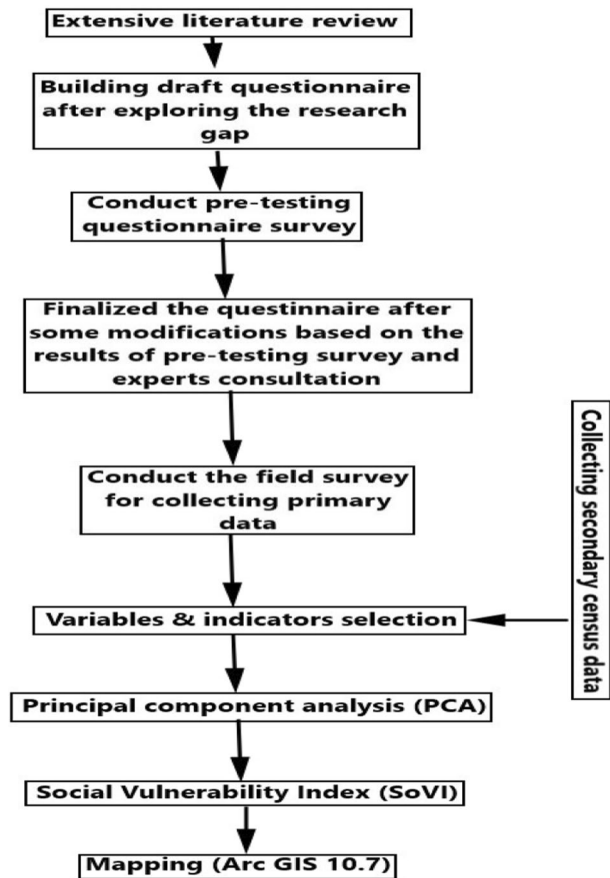
## 3 Results

### 3.1 Socio-demographic characteristics of the respondents

Table 2 shows the socio-demographic profile of the respondents of the study area. Only 6.2% of households are female-headed. The mean age of the respondent is 52.82 (SD ± 9.77). The mean household size is 4.46 (SD ± 1.75). About 16.29% of respondents are illiterate, most respondents (62.64%) have completed primary or secondary education which is their highest educational level and only 21.25% of respondents have achieved a college degree or higher education.

About 37.78% of interviewees live in the kutchra house built with poor housing material such as mud, straw, or leaves. The average landholding size is 1.34 (SD ± 2.14) ha, with more than 70% of the families owning up to 4 ha of agricultural land. The mean monthly income is US\$ 154.01 (SD ± 34.32). Occupation varies from the respondent to respondent. Although it is an agricultural-based country, only 18.15% of respondents lead their livelihoods by agriculture; 27.43% are day labor; small business (35.92%) is comparatively popular than other occupations among the respondents; and 14.83% are service holder. Only 3.72% of respondents are unemployed due to their old age, disability, and lack of employment opportunity.

**Fig. 2** The flowchart showing the research methodology



**Table 2** Socio-demographic characteristics of the respondents

Statistics	Mean	$\pm$ SD	Statistics	Percentage (%)
Age (years)	52.82	9.77	Female headed	6.2
Household size	4.46	1.75	Illiterate	16.29
Monthly income (US\$)	154.01	34.32	Primary or secondary education	62.64
			College or higher degree	21.25
Land (ha)	1.34	2.14	Occupation	
			Agriculture	18.15
			Day labor	27.43
			Small business	35.92
			Services	14.83
			Unemployment	3.72
			Kutchra house	37.78

### 3.2 Social Vulnerability Index (SoVI) for Chalna Municipality

A total of seven components with eigenvalues greater than 1.0 were extracted through PCA. The principal components explain 96.33% of the total variance of the data. Variables with maximum component loadings were identified as the main driver of the factors. All the commonalities were greater than 0.50. The Kaiser–Meyer–Olkin (KMO) test value was 0.65, and Bartlett's test of sphericity was significant at  $p < 0.05$ . This indicated that the variables used in this study were appropriate for PCA. Furthermore, the seven components were named based on loaded variables and their cardinality as follows: urban, occupation, and poor infrastructure; the vulnerable populations group; poverty; access to services; population density; lack of savings; and lack of proper sanitation. Brief descriptions of the seven components are shown in Table 3.

All seven components were summed to produce an overall SoVI score for each ward. The wards are also ranked according to their level of SV (Table 4). The results show that score with positive sign indicates a likely increase in SV and negative sign indicates a possible decrease in SV. The extent of vulnerability could be very high or very low based on the score. The overall SoVI scores range from 11.57 (most vulnerable) to  $-12.50$  (least vulnerable). Results reveal that the mean SV score of the area is 0.002 with a standard deviation of 7.74. The study found that five of the nine wards had a vulnerability score of the average vulnerability score. Ward 5 shows the highest vulnerability score, and ward 8 shows the lowest vulnerability score.

### 3.3 Factors influencing social vulnerability in Chalna Municipality

Figure 3 shows the spatial distribution pattern of the contribution of individual components that regulate the wards whether it is most vulnerable or least vulnerable. Individual components that jointly produced the SoVI score need to be highlighted. The main drivers of SV can be clearly understood through the assessment of individual components.

The first factor, urban, occupation, and poor infrastructure, contributes 30.063% with an eigenvalue of 9.921. The main factors affecting this component include a high percentage of population that use fuelwood as cooking material, the high percentage of households employed in agriculture, day labor and services, and the high percentage of households used house with the poor external wall. All these aforementioned variables are loaded with a positive sign. Thus, the first factor contributes to a higher SV and assigned a positive sign. The highest vulnerability is found in ward 5.

The second factor identifies the area with a high percentage of illiterate, elderly, children, and disabled persons. These variables are loaded with a positive value. Since these variables increase SV, a positive sign is assigned. The majority of the study units are located in low–medium to medium vulnerable categories. This factor explains 19.602% of the variance of the dataset.

The third factor, poverty, explains 13.139% of the variance and is driven by a high percentage of unemployment and income of less than \$1000. All of these variables are loaded with a positive value. This could result in higher SV. Therefore, a positive sign was attributed to the component. Ward 1 was found as the high poverty-driven ward.

The fourth factor, access to services, is driven by the number of health institutes that loaded positively on this factor. At the same time, the percentage of people live in an area

**Table 3** Results of principal components analysis (PCA) for developing SoVI of Chalna Municipality

No.	Component name	Eigenvalue	No. of drivers	Variables	Loading	Cardinality	Explained variance (percent households)
PC1	Urban, occupation and poor infrastructure	9.921	11	PRENTER PAGRI PLABOR PBUSINESS PSERVICE PFUEL PTV PNOEMBANKMENT PNOWATER PLOWALL PFEMWC AVGHH PAGE65 PAGE5 PDISABILITY PFEMLF PILLIT PNOCOLLEGE PRADIO PMOBILE	-970 .619 .719 -866 .691 .635 -706 -899 -938 .658 .958 .770 .614 .732 -654 -592 .746 -735 .707 -506	+	30.063
PC2	Vulnerable populations group	6.469	9			+	19.602

Table 3 (continued)

No.	Component name	Eigenvalue	No. of drivers	Variables	Loading	Cardinality	Explained variance (percent households)
PC3	Poverty	4.336	5	PFEMALE AVGLAND PUNEMPLOYED PINCOME	-.485 .575 .532 .500	+	13.139
PC4	Access to services	3.470	3	PNOELECTRICITY MEDAGE NCYCLONESHELTER	.591 .527 .687	-	10.514
PC5	Population density	2.911	3	NHEALTH PFMH PMORFAM	.527 .748 .665	+	8.821
PC6	Lack of savings	2.602	1	POPEN	-.479	+	7.884
PC7	Lack of proper sanitation	2.083	1	PNOSAVING PNOSEWER	-.811 .638	+	6.313

**Table 4** Level of social vulnerability of nine wards of Chalna Municipality

Rank	Ward	SoVI score	Vulnerability
1	5	11.57	High
2	2	7.66	Medium–high
3	6	4.08	Medium–high
4	4	3.95	Medium–high
5	7	–1.0	Medium
6	1	–1.80	Medium
7	9	–2.60	Medium
8	3	–9.34	Low–medium
9	8	–12.50	Low

N.B: SoVI figures are rounded to two decimal places

without cyclone shelters that negatively loaded. Both factors decrease SV. Therefore, a negative sign was assigned. This factor explains 10.51% of the total variance.

The fifth factor, population density, explains 10.82% of the total variance of the data. The component is driven by population density and size of the family. Densely population and larger family size in the same area are vulnerable to disaster because they would have more difficulty in the evacuation process, taking mitigation actions, preparedness, etc. Thus, the driver increases the SV and so a positive sign was attributed to it. Ward 4 was found as the densely populated area with high SV.

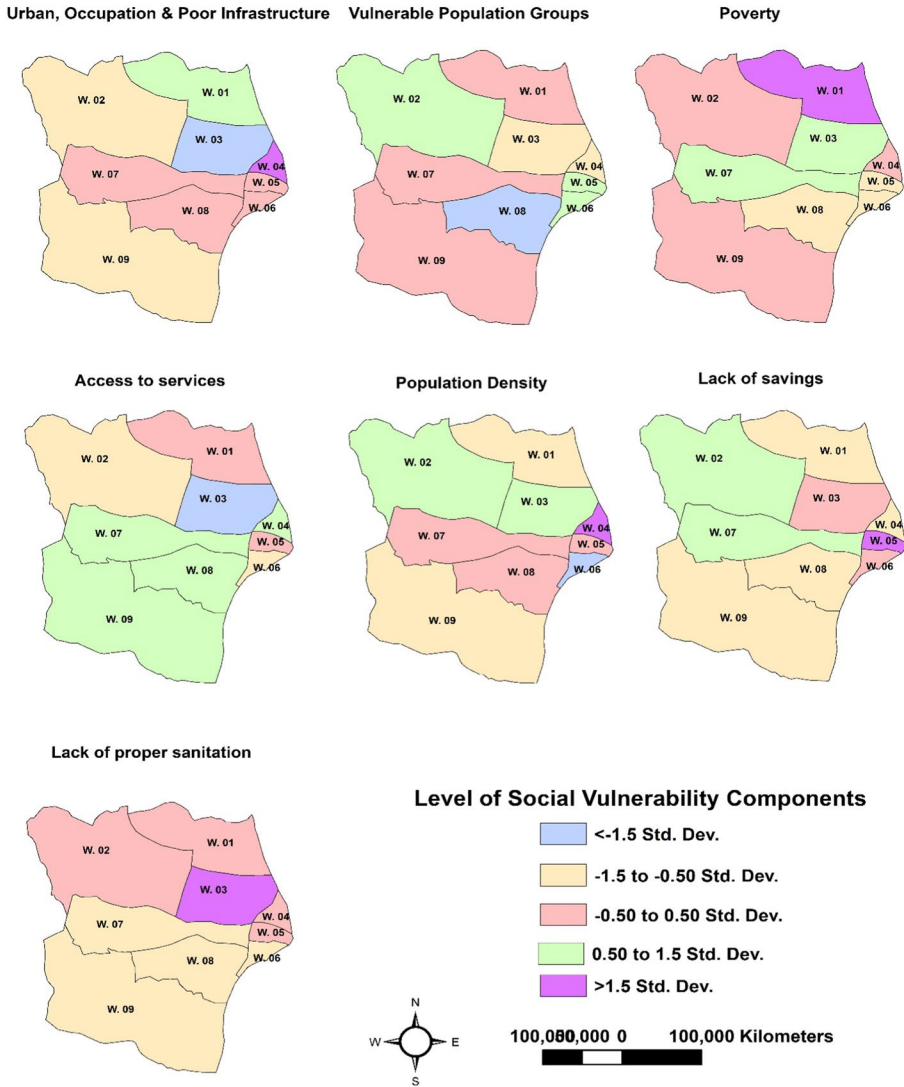
The sixth factor, lack of savings, explains 7.88% of the total data variance. The population without any proper saving would have faced economical difficulty during a disaster that increases SV. A positive sign is assigned to the factor identifying the populations with no savings for the last year. Ward 5 was found as the most vulnerable area due to a lack of savings.

The seventh factor, lack of proper sanitation, is driven by the percentage of people who have no adequate sewerage system. These people have passed a tough time to recover the impacts of a disaster. Overall, it increases the SV and a positive sign was assigned to it. Ward 3 was found as an elevated vulnerable area because of an inadequate sewerage system available in this area.

### 3.4 Spatial distribution of SoVI

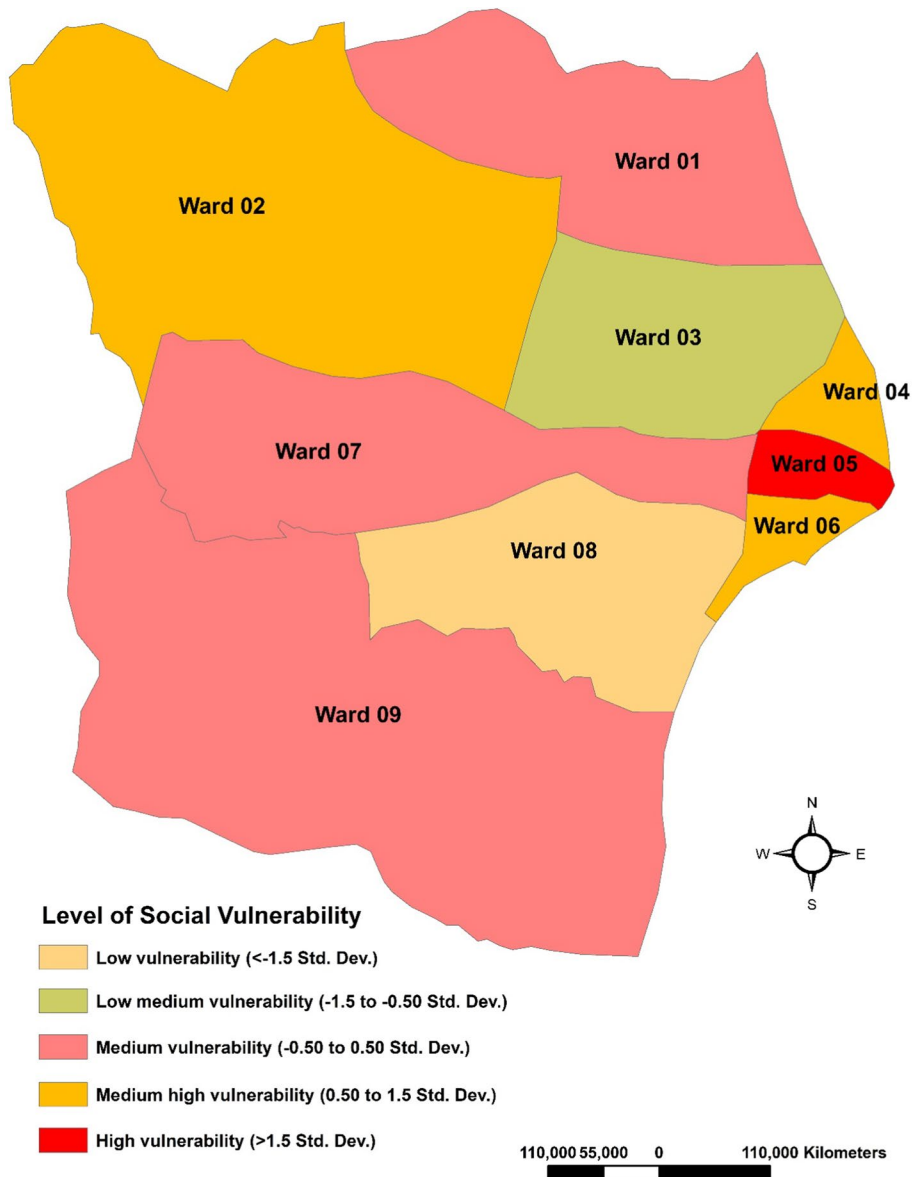
Figure 4 shows the spatial distribution of SV based on the SoVI of nine selected wards of CM. The ward which has SD greater than 1.5 is classified as most vulnerable, and the ward which has SD lower than –1.5 is classified as least vulnerable. All the wards (1, 2, 4, 5, 6, 7, and 9) except for wards 8 and 3 fall within the high to medium vulnerability category. Ward 8 is leveled as least vulnerable in the context of SV. Ward 8 ranked the lowest in SoVI.

Because of high-income status of its population, land value, low population density, the presence of the less vulnerable group, moderate savings, and comparatively adequate sewerage system (Fig. 4), the low–medium vulnerability score is observed in ward 3. Availability of agricultural employment, high access to services, e.g., radio, the presence of cyclone shelter, and embankment, and the less vulnerable group makes this ward low–medium category in social vulnerability index. A total of three (wards 1, 7, and 9) out of nine wards are classified as a medium level of vulnerability (–0.50 to 0.50 SD). These wards have



**Fig. 3** Spatial distribution of the extracted components found by PCA principally used for generating SoVI of the nine wards of Chalna Municipality

high vulnerability scores due to the urban, occupation, and poor infrastructure, poverty, the presence of vulnerable groups, and inadequate access to services. Around 33.34% (wards 2, 4, and 6) of the wards are demarcated into the classification of the medium–high level of vulnerability (0.5–1.5 SD). These wards fall into the medium–high category because of its high score from urban, occupation, poor infrastructure, vulnerable populations group, and population density (Fig. 4). Only one ward (ward 5) belongs to the high vulnerability category due to its high score for the presence of the vulnerable population group and a lack of savings.



**Fig. 4** Spatial distribution of the combined score of SV of the nine wards of Chalna Municipality found by SoVI

## 4 Discussion

Vulnerability assessment has been gained increasing attention in the scientific community as a guiding tool for decreasing the impacts of natural hazards and to encourage the community to be disaster resilient. However, academic communities are yet to decide on a unique definition of vulnerability due to its complexity. Therefore, such complexity makes



a hindrance for founding a general set of stable socioeconomic and demographic matrices for measuring vulnerability at diverse ranges (Cutter and Finch 2008; Kuhlicke et al. 2011). The indicator selection is an important factor to design SV and subject to data availability (Tapsell et al. 2010).

This study found using PCA that unplanned urban development, unstable occupation and poor infrastructure, vulnerable population groups, poverty, lack of access to services, population density, lack of savings, and lack of proper sanitation are some factors making the study area socially vulnerable. The driving forces behind SV show considerable spatial variation across the study area. In our study, it is noticed that ward 5 shows a high vulnerability. Furthermore, a high percentage of population > 5 years old and < 65 years old, female-headed household, single sector occupation, high dependency on nature for fuel, poor educational status, poor housing structure, and lack of enough savings are the main drivers of the high vulnerability of ward no. 5. In addition to this, wards 2, 6, and 4 also show medium–high vulnerability.

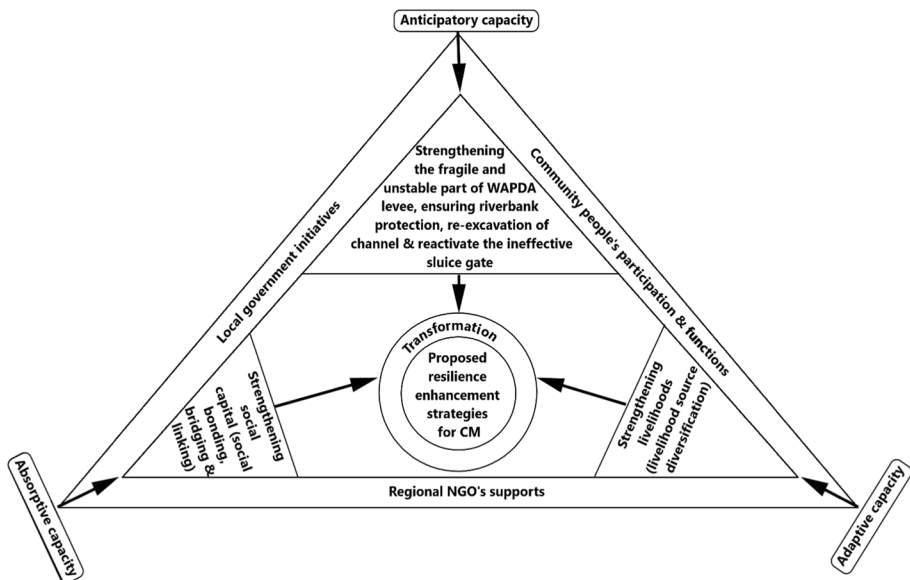
The results also reveal that most of the wards (seven wards out of nine) of CM rank high to medium in terms of SoVI score and two of them in the extreme (highest and lowest) group. The main reason is that these wards are located near the riverbank. The poor landless people live on governmental “Khas land” outside the water and power development authority (WAPDA) levee. They do not have any ability to survive in the high land beside the WAPDA levee because of high land prices. Since riverbank erosion is a continuous process and constantly affects the poor landless people. Moreover, they also face the scarcity of freshwater. The study area faces a high salinity problem. A higher salinity problem decreases the productivity of the land. This triggers a low annual yielding crop from barren lands. Maximum canals (Khals) of the municipality area are not only silted with alluvial soil but also maintain a nonfunctioning sluice gate. It creates the inundation problem in the wet season, but in the dry season, the nonfunctioning sluice gate also contributes to the severe salinity problem. Low poverty, high educational status, and good quality of housing structure are regulators of low vulnerability in ward no. 8. In contrast, other wards of the municipality exhibit opposite conditions. This pattern reflects an imbalanced development across the study area. The key causal factors include poor economic conditions, unstable income generating sources, poor infrastructure, lack of services, lack of adequate sewerage systems, etc. The aforementioned facts are treated as a key driver of the social vulnerability of the CM. Our result is similar to the findings of Chen et al. (2013), which exposed that unemployment, poverty, education, and family size are the drivers of SV in China. Boruff and Cutter (2007) reported that unplanned urban development, unstable occupation, and poor infrastructure were responsible for increasing SV in the Caribbean Islands. They further stated that people who used wood and charcoal rather than electricity for their cooking purposes pose more vulnerability in terms of the impacts of any upcoming disaster. Dunno (2011) found the same results as Boruff and Cutter (2007) that households' who used alternative fuels for food preparation are potentially more vulnerable than those who are using electricity. Cutter et al. (2003) and Chen et al. (2013) found similar results in our study that extreme age (under 5 or above 65 years), households' poverty, and illiteracy act as driving forces to increase the susceptibility of SV. Wright (2019) revealed that extreme age acts as a hindrance in the aspect of mobility during any disastrous events. Dunno (2011) revealed that elderly people who have retirement allowance are less vulnerable than the elderly who have no retirement allowance because they have monetary assistance by which they can take some precautionary actions for lessening the vulnerability. Frigerio et al. (2018), Chen et al. (2013), and Cutter et al. (2003) found the similar results as this study that females are more vulnerable than males as they lack information and wealth and have more family

care responsibilities, and for this reason, the female mortality rate is higher than the male mortality rate during any disaster event. Apotsos (2019) found that extreme age, poor educational status, low income, and unemployment are the main drivers of SV in South Africa, which is similar to our findings. Quder et al. (2017) reported that people who live in the far distance from cyclone shelters pose more vulnerability than those who live nearby, which is similar to our findings.

Bangladesh is extremely vulnerable to climate-induced natural hazards such as tropical cyclones, tidal surges, tidal floods, riverbank erosion, and salinity intrusions that expose the country to an irreparable loss (Islam et al. 2014, 2016). To adapt to the riverbank erosion and salinity intrusion, the households take several adaptation strategies like they temporarily shifted to the high land beside the WAPDA levee for emergency shelter. Most of the respondents try to plant diverse crops and vegetables to adapt to high salinity problems. Different varieties of crops and vegetables like sunflower, watermelon, pumpkin, cucumber, corolla, etc., were farmed. Almost all households are involved in livestock (cow, goat, sheep, poultry, and pig) rearing. By this, they maintain the nutritional value at the family level and ensure economic solvency. Poor people can obtain the loan from NGOs and money lenders in critical emergency conditions (Islam et al. 2020).

Resilience is the ability of local communities, mainly obtained from interlinked absorptive, anticipatory, and adaptive capacities for dealing with stresses and distresses (Fig. 5). Communities with adaptive capacity can recover by lessening their vulnerability to similar distress and disturbance, which frequently occur, as well as to new and emerging risk (UNISDR, 2005). The three key drivers of social vulnerability in the study area, such as poor economic conditions, unstable income generating sources, and lack of services, would be diminished by increasing adaptive capacity.

Strengthening the anticipatory capacity can be possible through a proper range of preparedness and planning (Kellett and Peters 2014). It would be done by restoring the fragile



**Fig. 5** The proposed model for resilience enhancement in the study coastal area

and unstable part of the WAPDA levee by soil–cement blocks pilling and afforestation, ensuring riverbank protection by pilling sandbags and re-excavation of the channel by dredging and reactive ineffective sluice gates. Two key drivers of social vulnerability in the study area, such as unplanned urban and poor infrastructure and lack of adequate sewage systems, would be reduced by increasing anticipatory capacity.

Absorptive capacity is the capability of the social system in which existing skills and resources are used to handle and control any disaster, emergencies, or adverse conditions (Hudner and Kurtz 2020). Social capital plays a vital role in strengthening the absorptive capacity. Social bonding, bridging, and linking are three main factors of absorption capacity.

The transformation is a basic change in the deep structures that trigger or enhance vulnerability and risk as well as how risk is shared within communities (O'Brien 2012). The transformation mainly includes strategic thinking and policy, empowerment, leadership as well as innovation. People's capacity to adapt, anticipate, and absorb shocks can be built, reshaped, and enhanced by the transformation process.

Figure 5 shows the proposed model for resilience enhancement in the CM. This transformation process and their outcomes indicate that the communities' capacity to change the causes of their exclusion has been enhanced. However, the combined efforts of the government (GO), NGOs, and local authorities are of urgent need. If there are mutual collaboration and coordination in the three basic groups (GO, NGOs, and local people), the resiliency will meet the near future in CM, Dacope upazila, in southern coastal Bangladesh.

All of the above-discussed factors impact the fragile landscape in the coastal region of Bangladesh. However, the key shortcoming of this work is that this analysis excludes some regulating factors of SV, such as population change, race and ethnicity, and disaster information dissemination via sign/symbolic language. This study presents a local-level intelligible assessment of SV, which helps the practitioners to take early initiatives for lessening disaster risks and vulnerability. However, many disasters also occur in other regions of the country, including flooding, drought, landslide, and so on. Future work requires to be conducted to construct a SoVI on the entire geographic area of the country.

## 5 Conclusions

This study intends to construct a household ward-level SV at the microscale in the CM of southwest coastal Bangladesh by applying SoVI. In this study, we provide outcomes of SV for each indicator as well as for SoVI scores over the southwest coastal region at the household ward level, which demonstrates an interesting spatial distribution pattern. The findings of this work, thus, confirm the idea that vulnerability is not only naturally deterministic but also socially developed interaction. The SV must be combined into the understanding of the interactions that make people exposed to potential risks related to hazards. The outcomes of this work are crucial for the decision-makers to effectively develop a systematic policy for the studied municipality as well as the entire coastal region that absence composite social assets to adapt for areas that absence definite social capital, as confirmed by our work. Hence, a vulnerability reduction plan should pay more attention to occupational diversification and make alternative livelihood options for coastal people who suffer in a vulnerable condition. Decision-makers should, for example, take a step to focus on the population-based issue in areas, whereas they address a composite SV in the coastal region. CM should upgrade social resilience to natural hazards as proposed resilience model

informed by this study. By giving most socially susceptible areas in three wards (2, 4, and 6) among all wards, our analysis provides helpful information for the respective authorized bodies at the regional and local scales such that in any level, they are informed about what forecasters make those wards susceptible and which ward needs prioritized aid for disaster preparedness. The study also clarifies that the utility of SoVI can be used in measuring SV in other regions of the world. The findings of the study provide scientific insight for taking actions for mitigating and preventing future coastal disasters in Bangladesh.

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## Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.


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