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Understanding Household Flood Adaptation Responses and Their Determinants in Manipur's Central Valley, India

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Abstract

This study examines household-level flood adaptation strategies and the factors influencing their adoption in the Central Valley of Manipur, a region highly prone to recurrent flooding. A quantitative research design was adopted, with data collected from 444 households using structured questionnaires. The household survey was supplemented by focus group discussions and key informant interviews to provide additional insights and contextual understanding. A binary logistic regression model was employed to identify the determinants of adaptation behaviour. The findings reveal that households primarily adopt low-cost, readily implementable measures — such as storing important possessions above expected flood levels (86%) and shifting valuable assets to higher floors (81.5%) — whereas resource-intensive measures show lower adoption rates; only 15.1% of households installed pumps to remove floodwater. The regression analysis indicates that awareness of flood risk maps, participation in preparedness drills, income, perception of escalating future flood impacts, and older age (marginally significant) positively influence adaptation, whereas flood anxiety negatively affects adoption. The study highlights the critical role of risk perception, socio-economic capacity, and institutional support in shaping household responses to flood hazards. The findings emphasise the need for improved risk communication, enhanced community-based preparedness programmes, and targeted policy interventions to strengthen resilience at the household level. This study addressed the gap in household-level flood adaptation research in Manipur and provides insights for climate adaptation in flood-prone regions of Northeast India and South Asia.

Keywords: Flood adaptation; household resilience; binary logistic regression; risk perception; Manipur; Central Valley

1. Introduction

The environment gives us valuable resources as well as potential threats like natural disasters (Abegaz et al., 2024). Societal progress or development, including social, economic, cultural, and demographic dimensions, is disrupted by catastrophic events. It often results in human, socio-economic, and environmental losses that exceed the recovery capacity of affected communities (Hannah et al., 2022; UNISDR, 2012). Among all extreme disaster events, the most destructive and frequent disaster is floods. They claim numerous human lives and inflict severe economic losses worldwide (Alderman et al., 2012; Cohen M., 1993; Dangulla et al., 2020; Doocy et al., 2013; Glago F. J., 2021; Jonkman et al., 2024; Motta et al., 2021; Sahu et al., 2021; Salazar-Briones et al., 2020; Yu et al., 2022). Moreover, flood impacts are aggravated by climate change and have caused significant loss of livelihoods, lives, and property damage (Intrieri et al., 2019). Previous studies also reveal that the intensity and frequency of floods are expected to increase in the age of climate change (IPCC, 2023). It is expected that flood risks will be intensified by the overall effects of climate change and socio-economic growth (Bubeck et al., 2012). Considering these facts, there is an urgent need for robust and comprehensive adaptation strategies to mitigate the impacts of floods.

Most adaptation measures adopted so far have followed a top-down approach, where external actors make decisions. However, this approach is increasingly criticised for lacking efficiency and equity in outcomes (Pisor et al., 2022; Oliver et al., 2023). In contrast, citizen-led adaptation, also called bottom-up, autonomous, or community-based adaptation, is considered a better approach as it allows people who are directly affected by climate change to decide their own adaptation goals and strategies (Oliver et al., 2023; Forsyth, 2013). Usually, top-down adaptation takes place at national, regional, or city levels, while citizen-led adaptation mainly occurs at the community or household level (Berrang-Ford et al., 2021). Citizen-led approaches give power and decision-making authority to local communities. They can also be more effective because they use local and indigenous knowledge, address locally important drivers of risk, and avoid unacceptable limitations and trade-offs (Petzold et al., 2020). Although household-level adaptation has limits in reducing overall risk, it provides a direct, scalable, and quickly applicable way to build resilience. This is especially important in low- and middle-income countries, where large-scale adaptation is often constrained by institutional and governance limitations (Petzold et al., 2023; Kreibich et al., 2015).

Recently, traditional flood management strategies have undergone a significant paradigm shift. Nowadays, households are increasingly adopting adaptation measures to reduce flood impact. These measures help in strengthening the resilience of people living in flood-prone areas. They are an important part of modern flood risk management. Many studies have examined how effective these measures are, how widely they are adopted (Hudson et al., 2014; Hudson et al., 2019; Poussin et al., 2015; Valois et al., 2019; Ejeta et al., 2015), and the factors that influence their adoption. These factors encompass socio-demographic aspects such as income, household composition, and homeownership; psychological aspects like risk and vulnerability perception; and experiential aspects such as whether a household has experienced flooding or not. These are commonly included in studies on flood adaptation (Huang et al., 2020; Eryılmaz and Hırca, 2021; Miceli et al., 2008; Bronfman et al., 2019; Terpstra, 2011).

The work of Otum Ume et al. (2020) stressed the pivotal role of household-level responses to climate hazards such as floods in fostering a climate-resilient society. Their research established households as primary adaptation agents, simultaneously bearing climate change impacts and possessing the capacity for meaningful action. Duzi et al. (2017) also identified different factors that control the adaptation measures in the Becva River of the Czech Republic. Their work highlighted the importance of socio-economic factors in the adoption of household adaptive measures in the region. The study of Mondal et al. (2021) analysed the different factors influencing household adaptation measures implemented in northern Bangladesh after the flood of 2017. Their results indicate the perceived probability of flood, perceived preparedness, flood experiences, flood exposure, membership, household head's sex, education, source of income, and land ownership as the main drivers of household adaptation measures adopted. In a similar way, Rahman et al. (2024) performed a holistic assessment of flood preparedness in two flood-prone rural regions of Dowarabazar Upazila and Sunamganj District of Bangladesh. Their findings show a low level of adaptation in the study area. Additionally, the main factors determining flood preparedness in the regions include gender, occupation, age, monthly income, multiple sources of income, and house type.

In the context of India, a comprehensive review by Pakhale and Nale (2023) examining flood risk assessment advancements in India from 1951 to 2020 revealed a significant data gap at the household level, hampering effective policy formulation. Their analysis showed how flood events have shaped evolving policies, actions, and risk assessment improvements while highlighting the critical need for reliable household-level data. Recent research by Rehman and Sajjad (2024) in West Bengal's Bhagirathi Sub-basin uncovered diverse adaptation strategies influenced by caste and gender, linking flood adaptation to broader sustainable development goals. In the context of Manipur, Sanayanbi et al. (2020) measured flood vulnerability at the district level in the state. However, there is no significant research on household-level flood adaptation and the factors influencing it in Manipur. Therefore, the current research will focus on identifying the various adaptation measures adopted in the Central Valley of Manipur and the factors influencing them. The findings will contribute to both immediate flood management strategies and long-term climate adaptation planning, offering a replicable model for similar regions in India facing increased flood risks under climate change. The specific objectives of the study include: (1) To identify the types of household flood adaptation measures adopted in the Central Valley; (2) To determine the socio-economic and psychological factors influencing adaptation behaviour; (3) To provide evidence-based policy recommendations.

2. Materials and methods

2.1. Study area description

Manipur, situated in north-eastern India (23°50′N to 25°42′N and 92°58′E to 94°45′E), covers an area of 22,327 sq. km. It is administratively divided into sixteen districts. The state is largely mountainous, with about 90% of its terrain consisting of hills, while the remaining 10% forms the central valley. The study area is the Central Valley of Manipur, also known as the Imphal Valley (Fig. 1). It comprises five districts, namely Imphal East, Imphal West, Bishnupur, Thoubal, and Kakching. Nearly 60% of the state's population, out of 2.57 million, lives in this valley (Census of India, 2011).

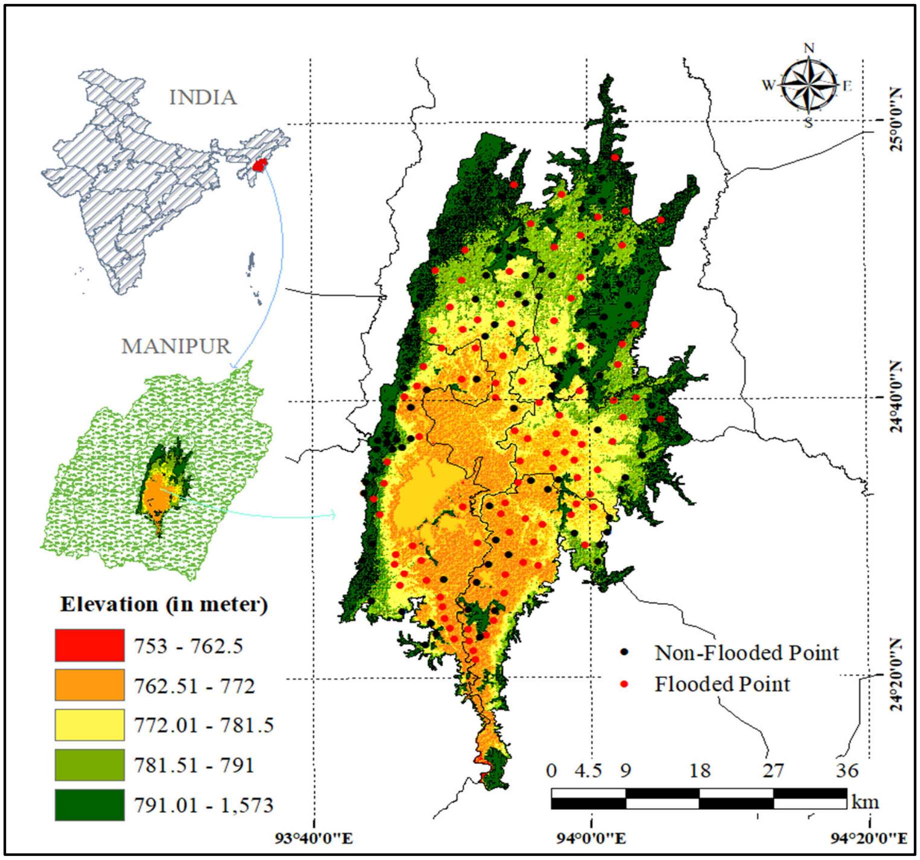


Fig. 1. Central valley of Manipur, India

It serves as both the demographic and agricultural core, making it an important part of the state for livelihoods as well as economic activities. Located at the centre of the state, the valley has a gentle north-to-south slope. Major rivers of the state, such as Imphal, Iril, and Thoubal, flow through this valley. During the monsoon season (June to September), these rivers and their tributaries frequently overflow and breach embankments, leading to severe flooding. The region experiences a subtropical monsoon climate (Cwg) (Manglem, 2021), with an average annual rainfall of 1,473.44 mm. There is marked seasonal variation between dry winters and wet monsoons. Historically, the region is prone to flooding (1916, 1929, 1941, 1953, 1965, 1966, 1989, 1992, 1997, 1998, 1999, 2001, 2015, 2017, 2019, 2020, 2024 and 2025). These flood events result in substantial losses of life, property, and agricultural output (Sharma and Singh, 2026). For example, the floods of 2024 and 2025 affected all the valley districts of Manipur. They caused widespread impacts on houses, infrastructure, fisheries, and animal husbandry activities (MSDMA).

2.2 Research Design and determination of sample size

While collecting data on household-level flood adaptation of the flood-affected areas, the study used a mixed-methods research design. Qualitative data were collected from 5 focus group discussions (FGDs) and 8 key informant interviews (KIIs) with community leaders, inhabitants and former elected representatives. The participants were selected purposely to represent a range of opinions regarding the various adaptation measures employed. The information gathered from FGDs and KIIs was cross-verified with the results of data collected from the survey. By doing this, the findings of the quantitative data can be validated and improve the understanding. The qualitative part helps to explain why people prefer certain adaptation methods and how social and institutional factors influence their behaviour. The questionnaire contains both open-ended and closed-ended questions. It comprehensively assessed the households' flood experience, risk perception, preparedness for flood, adaptation measures adopted, information sources and community engagement, demographic data and socio-economic characteristics.

A cross-sectional multistage sampling technique, encompassing a systematic sampling method, was used to ensure a representative sample of the flood-affected population across the valley districts. Localities significantly impacted by flooding were identified based on historical and recent flood data available on the internet, as well as government reports. Surveys were conducted in these areas, and the sample size was selected to represent the population properly, with the number of households from each locality chosen in proportion to its total number of households. The sample size was determined using Cochran's formula for an unknown population, which is commonly used for calculating sample sizes in surveys with an unknown population proportion (Equation 1).

$$n_o = \frac{z^2pq}{e^2} \tag{1}$$

Where,

n_o = sample size
z = selected critical value of desired confidence level
p = estimated proportion of an attribute that is present in the population
q = 1- p
e = desired level of precision

The required sample size at 95% confidence level and 5% margin of error is 384.16 = 385. But we conducted 444 household surveys, which is slightly more than the required sample size. This provides sufficient data for a strong statistical analysis that can represent the targeted areas. Quantitative data were obtained through systematic sampling using a semi-structured questionnaire. This sampling strategy helped in ensuring the accurate representation of households' flood experience, risk perception, preparedness for flood, adaptation measures adopted, information sources and community engagement, demographic data and socio-economic characteristics of the flood-prone areas.

2.3 Survey instruments

Data were collected from July to October, 2025. A pilot survey of 50 households was conducted before the main survey to test the questionnaire and data collection procedure. To reduce data entry errors, data were processed using both SPSS and Microsoft Excel. To assess households' flood coping strategies, respondents were asked if they had implemented certain adaptation measures. These adaptation measures are generated after a thorough review of the literature and consider only those applicable in the study area. Moreover, to supplement and validate those measures, FGDs and KIIs were also carried out. The details of these adapted measures are given in Table 4 and Fig. 2(a).

2.4 Explanatory variables

Multiple factors influenced coping strategies. So, there is no universally accepted framework for selecting explanatory variables. The dynamics of household vulnerability influenced the adoption of certain measures. For this study, the different explanatory variables include flood experienced (last 5 years), awareness of the flood risk map, work/income loss (last 5 years), flood anxiety, participation in flood preparedness awareness drill/sessions, age, gender, education, family size, income and perceived future flood impacts (Table 1).

Table 1: Explanatory variables used in the study

Variables	Description	Mean	Std. deviation
Flood experienced (last 5 years)	0 = No, 1 = Yes	0.97	0.18
Awareness of the flood risk map	0 = No, 1 = Yes	0.13	0.34
Work/income loss (last 5 years)	0 = No, 1 = Yes	0.86	0.35
Flood anxiety	1 = Very low, 2 = Low, 3 = Moderate, 4 = High, 5 = Very high	3.79	1.07
Participation in flood preparedness awareness drill/sessions	0 = No, 1 = Yes	0.10	0.31
Age	1 = Below 30, 2 = 30 to 40, 3 = 40 to 50, 4 = 50 to 60, 5 = Above 60	4.17	0.92
Gender	1 = Male, 2 = Female	1.23	0.42
Education	1 = No formal education, 2 = Below 8, 3 = 8 to 12, 4 = 12 to Graduate, 5 = Above Graduate	2.89	1.06
Family size	0 = Less than 7, 1 = 7 to 12, 2 = More than 12	0.41	0.53
Income	1 = Below 10,000, 2 = 10,000 to 20,000, 3 = 20,000 to 40,000, 4 = Above 40,000	2.61	0.99
Perceived future flood impacts*	1 = Lesser, 2 = Same, 3 = Greater, 4 = Much greater, 5 = Don't know	3	1.39

**Don't know* category was used as the reference group in regression.

2.5 Flood adaptation strategies using a logistic regression model

This study assessed household adaptation strategies in flood-prone areas of Manipur's Central Valley. A binary variable (1 or 0) was assigned for each adaptation measure to denote household adoption. Firstly, the total number of adaptation measures (out of 8 measures) adopted by each household is generated. Then, the median across all households was derived, resulting in a value of 4. Based on the median threshold, households adopting four or more measures were coded as 'adopters' (1), while those adopting fewer than four measures were coded as 'non-adopters' (0). This approach was adopted because some measures were easy to implement, and almost all households adopted at least one adaptation measure. Using SPSS Statistics 21, data gathered from surveys were analysed. Multicollinearity test and binary logistic regression analyses were performed to assess the relationships between dependent and independent variables.

The adoption of at least four measures was the dependent variable in the logistic regression model. A binary logistic regression model was applied to identify the factors influencing households' adoption of adaptation measures. The model is given as:

$$Logit\ (Px) = \log\ (P_x / (1 - P_x)) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots\ldots + \beta_j x_j$$

Where,

Px = Probability of adopting adaptation measures

$1 - P_x$ = Probability of not adopting adaptation measures

$\beta_1, \beta_2, \beta_3, \ldots.., \beta_j$ = Coefficient of the explanatory variables.

$x_1, x_2, x_3, \ldots.., x_j$ = Explanatory variables.

The dependent variable was coded as a binary outcome in the model specification (1 = adopter of four or more adaptation measures; 0 = adopter of less than four adaptation measures). Based on the coding scheme outlined in Table 1, the independent variables were categorised as nominal or ordinal predictors (table 2).

Table 2: Independent variables and their units of measurement

Sl. No.	Independent Variables	Unit of measurement
1	Flood experienced (last 5 years)	Categorical (Nominal)
2	Awareness of the flood risk map	Categorical (Nominal)
3	Work/income loss (last 5 years)	Categorical (Nominal)
4	Flood anxiety	Categorical (Ordinal)
5	Participation in flood preparedness awareness drill/sessions	Categorical (Nominal)
6	Age	Categorical (Ordinal)
7	Gender	Categorical (Nominal)
8	Education	Categorical (Ordinal)
9	Family size	Categorical (Ordinal)
10	Income	Categorical (Ordinal)
11	Perceived future flood impacts	Categorical (Ordinal)

For instance, flood experience was coded as 0 = No and 1 = Yes; gender was coded as 1 = male and 2 = female, age was classified into five groups (1 = Below 30, 2 = 30 to 40, 3 = 40 to 50, 4 = 50 to 60, 5 = Above 60), and flood anxiety was coded as 1 = Very low, 2 = Low, 3 = Moderate, 4 = High and 5 = Very high. This standardised coding framework ensured uniformity across variables and enabled each coefficient (β) to be interpreted as the change in the log-odds of adopting adaptation measures relative to the reference category. To ensure the reliability of the results, the model specification adopted established procedures for binary logistic regression (Hosmer et al., 2013), including checks for multicollinearity and goodness-of-fit. Using a structured questionnaire, proper statistical methods, and a clear modelling approach made the study's results more reliable and stronger. Before performing logistic regression analysis, correlation analyses were conducted among variables to examine the association between them and to identify potential multicollinearity. These associations should not be interpreted as evidence of causality. Given the cross-sectional nature of the data, the results should be treated as associative rather than causal.

3. Results

3.1 Socio-demographic profile of the households

The socio-demographic characteristics of the households, including age, gender, education level, family size, source of livelihood, and monthly income, are presented in **Table 3.**

Table 3: Socio-demographic profile of households in the study area

	Frequency	Percentage (%)
Age		
Below 30	3	0.7
30-40	17	3.8
40-50	88	19.8
50-60	130	29.3
Above 60	206	46.4
Gender		
Male	341	76.8
Female	103	23.2
Education		
No formal education	70	15.8
Below 8	53	11.9
8 to 12	188	42.3
12 to Graduate	121	27.3
Above Graduate	12	2.7
Family size		
Less than 7	272	61.3
7 to 12	163	36.7
More than 12	9	2
Source of livelihood		
Agriculture	117	26.4
Daily wage earner	88	19.8
Business	103	23.2
Govt. service	108	24.3
Others	28	6.3
Monthly income		
Below 10,000	65	14.6
10,000-20,000	142	32
20,000-40,000	137	30.9
Above 40,000	100	22.5

The majority of household heads are above 60 years of age (46.4%). Only a very small proportion of household heads are younger than 40 years. This indicates the domination of older household heads in the study area. In terms of gender, household heads are dominated by males (76.8%) compared to their female counterparts (23.2%). Regarding education level, the largest proportion of household heads (42.3%) completed their education between classes 8 and 12. A notable proportion (15.8%) have no formal education, while only 2.7% have education above the graduate level, indicating moderate educational attainment in the study area. The majority of households have fewer than seven family members (61.3%). Agriculture is the main source of livelihood for households (26.4%), followed by government service (24.3%)**,** business (23.2%)**,** and daily wage earner (19.8%). 6.3% are engaged in other occupations, such as tailor, writer, private job, private school teacher, etc. Finally, most households fall within the middle-income group (32% for 10000-20000 and 30.9% for 20,000–40,000).

3.2 Household adaptation strategies

The surveyed households adopted different adaptation measures across the study area. In the questionnaire, eight different adaptation measures were included, and every household was asked whether they had adopted that particular measure or not. The detailed data regarding these measures are presented in Table 4 and Fig. 2 (a). The results show that simple and easily implementable measures, such as storing important possessions above expected flood levels (86%) and shifting valuable assets to higher floors (81.5%), are highly adopted. Other measures adopted by more than half of the households include raising the foundation (64.6%) and strengthening the foundation (52.7%) of houses. In contrast, measures that require more resources, including installing pumps to remove floodwater (15.1%), storing emergency food and water supplies (38.3%), and maintaining designated refuge areas (24.5%), have low adoption rates.

Table 4: Different adaptation measures adopted in the study area

Sl. No.	Adaptation measures	Adopted (%)	Not adopted (%)
1	Raising foundation	64.6	35.4
2	Strengthening foundation	52.7	47.3
3	Water-resistant material	41.2	58.8
4	Pump installation	15.1	84.9
5	Installing a refuge zone	24.5	75.5
6	Storing important possessions above expected flood levels	86	14
7	Storing emergency food and water supplies	38.3	61.7
8	Storing valuable assets to higher floors	81.5	18.5

The number of adaptation measures adopted by each household is presented in Table 5. A total of 7 households (1.6%) do not adopt any adaptation measures. On the other hand, 93 (20.9%) and 81 (18.2%) households adopted 3 and 4 adaptation measures, respectively. Only 3 households (0.7%) adopted all the measures. Moreover, the median of number of adopted adaptation measures is 4, and the standard deviation is 1.8.

The district-wise profile of different adaptation measures is shown in Fig. 2(b). The adaptation measures adopted vary across the study area. For example, the most adopted measure of Imphal East (89.2%), Imphal West (87.5%) and Kakching (80.4%)

is storing important possessions above expected flood levels, while storing valuable assets on higher floors is the most adopted measure in Bishnupur (100%). Raising the foundation of households and storing valuable assets above expected flood levels (70% each) are the most adopted ones in the Thoubal district. On the other hand, installing pumps to drain floodwater is the least adopted measure in the districts of Imphal East (91.4%), Imphal West (85.9%), and Kakching (82.4%). For Thoubal (81.7%) and Bishnupur (78.8%), building a designated refuge zone is the least adopted measure. Use of water-resistant materials was adopted by 41.2% of households, placing it among the moderately adopted measures.

Table 5: Intensity of adaptation measures adopted by households

Intensity of adaptation	Frequency	Percentage
0	7	1.6
1	18	4.1
2	69	15.5
3	93	20.9
4	81	18.2
5	69	15.5
6	62	14
7	42	9.5
8	3	0.7
Total	**444**	**100.0**
Median	**4**	
Standard deviation	**1.8**	

3.3 Factors influencing household adaptation

Multicollinearity test among the independent variables was performed using Variance Inflation

Table 6: Multicollinearity test result

Variables	Tolerance	Variance Inflation Factors (VIFs)
Flood experienced (last 5 years)	.867	1.154
Awareness of the flood risk map	.955	1.047
Work/income loss (last 5 years)	.779	1.283
Flood anxiety	.802	1.247
Participation in flood preparedness awareness drill/sessions	.965	1.036
Age	.877	1.141
Gender	.909	1.101
Education	.760	1.316
Family size	.808	1.237
Income	.784	1.275
Perceived future flood impacts	.921	1.086

Factors (VIFs) and tolerance values before conducting logistic regression. All VIFs are less than 5, and the tolerance values are greater than 0.20. This confirmed that there was no serious multicollinearity among the independent variables. The details of the test are given in Table 6. Then, the model goodness-of-fit was analysed before model estimation by the chi-square test ($\chi^2 = 55.023$, $p < 0.001$), Cox & Snell ($R^2 = 0.117$) and

Nagelkerke ($R^2 = 0.157$) values, classification accuracy (67.1%) and the Hosmer–Lemeshow goodness-of-fit test ($p > 0.05$), indicating the reliability of the predictive performance. These results confirmed that the model adequately fits the data. The adopters and non-adopters of adaptation measures can be reliably distinguished by the predictors.

Binary logistic regression was used to determine the factors influencing the adoption of adaptation measures. Eleven independent variables were included in the model, viz. flood experienced in the last 5 years, awareness of the flood risk map, work/income loss in the last 5 years, flood anxiety, participation in flood preparedness awareness drill/sessions, age, gender, education, family size, income and perceived future flood impacts. Table 7 shows the result of the binary logistic regression analysis.

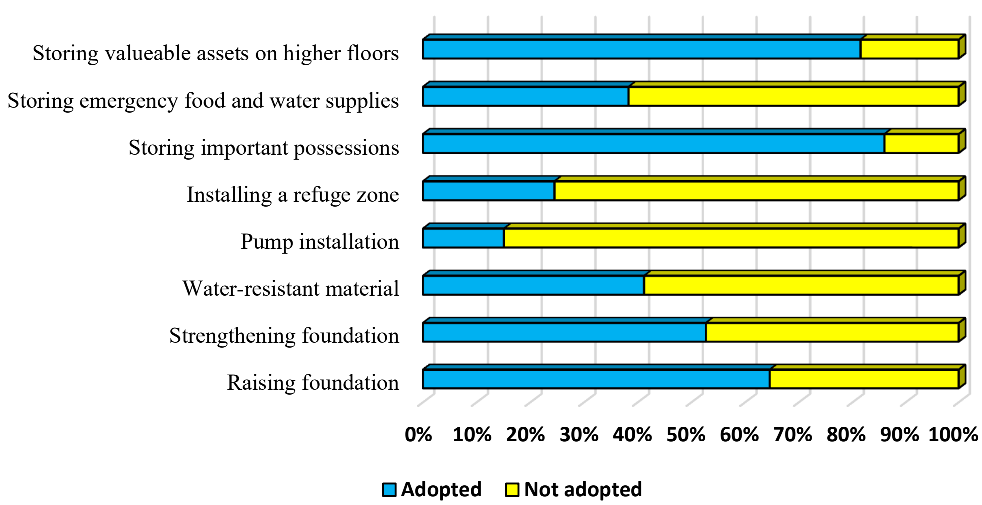
Table 7: Logistic regression results on adaptation measures adoption

Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Flood experienced (last 5 years)	0.062	0.614	0.010	1	0.920	1.064	0.319	3.543
Awareness of the flood risk map	0.675	0.337	4.025	1	0.045**	1.965	1.016	3.800
Work/income loss (last 5 years)	0.485	0.338	2.059	1	0.151	1.625	0.837	3.152
Flood anxiety	-0.437	0.114	14.702	1	0.001***	0.646	0.516	0.808
Participation in flood preparedness awareness drill/sessions	0.991	0.379	6.843	1	0.009***	2.695	1.282	5.665
Age	0.217	0.120	3.291	1	0.070*	1.242	0.983	1.571
Gender	-0.017	0.254	0.005	1	0.945	0.983	0.598	1.616
Education	-0.007	0.111	0.005	1	0.946	0.993	0.799	1.234
Family size	-0.290	0.216	1.801	1	0.180	0.748	0.489	1.143
Income	0.365	0.118	9.472	1	0.002***	1.440	1.142	1.816
Perceived future flood impacts								
Lesser	0.397	0.341	1.360	1	0.244	1.488	0.763	2.901
Same	0.294	0.315	0.874	1	0.350	1.342	0.724	2.487
Greater	0.881	0.318	7.656	1	0.006***	2.412	1.293	4.501
Much greater	1.040	0.349	8.860	1	0.003***	2.830	1.427	5.613
Don't know (ref)								
Constant	-0.870	0.894	0.947	1	0.330	0.419		

Notes: * Significance level at 90% ($p < 0.1$); ** Significance level at 95% ($p < 0.05$); *** Significance

The table reveals that six independent variables made a unique, statistically significant contribution to the model. They include awareness of flood risk map, flood anxiety, participation in flood preparedness awareness drill/sessions, age, income, and perceived future flood impacts. Awareness of flood risk maps had a positive effect ($B = 0.675$, $p = 0.045$), which means that households who know about flood risk maps are more likely to take adaptation measures. In contrast, flood anxiety had a strong negative effect ($B = -0.437$, $p = 0.000$), indicating that higher flood anxiety significantly reduces the likelihood of taking adaptation measures. Participation in flood preparedness awareness drill/sessions was positively associated with taking adaptation measures, with Exp(B) = 2.695 and p = 0.009. This indicates that households participating in awareness drills are 2.7 times more likely to adopt adaptation measures. Age was also a significant predictor, with older household heads increasing the odds of adopting adaptation measures (B = 0.217, p = 0.07). And income was also positively related to taking adaptation measures, with Exp(B) =1.44, p = 0.002. This suggests that higher-income households are 1.44 times more likely to adopt adaptation measures. Finally, two categories of perceived future flood impacts were significant predictors relative to the reference category ('Don't know'). Households perceiving future floods as greater (Exp(B) = 2.412, p = 0.006) and much greater (Exp(B) = 2.830, p = 0.003) are 2.4 and 2.8 times more likely to adopt adaptation measures, respectively. In contrast, the 'Lesser' (p = 0.244) and 'Same' (p = 0.350) categories were not statistically significant, indicating that only households with a distinctly elevated perception of future flood severity — rather than those expecting similar or reduced impacts are more likely to act.

(a)



(b)

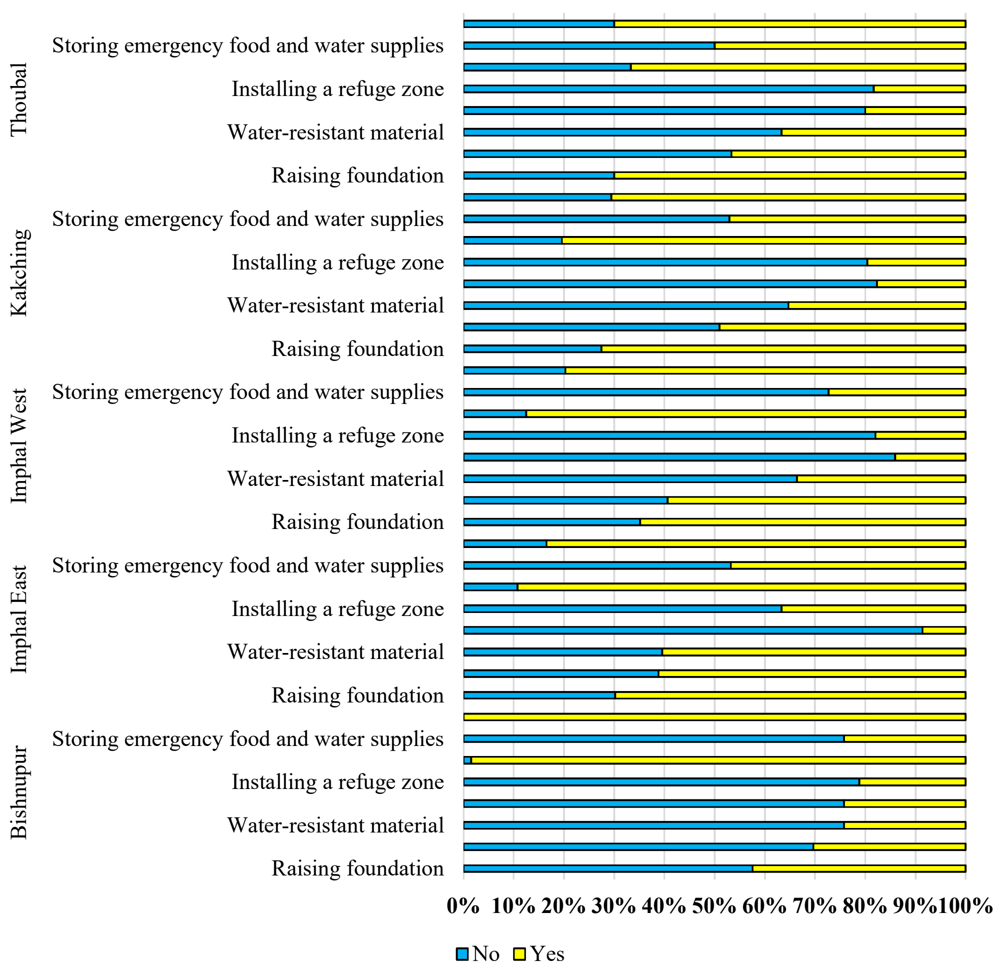


Fig. 2. (a) Graphical representation of different adaptation measures adopted (b) District-wise profile of different adaptation measures adopted .

Overall, the regression result shows that socio-demographic characteristics (income and age), risk perception and psychological factors (perceived future flood impacts and flood anxiety), and institutional/informational factors (participation in preparedness drills and awareness of flood risk map) play a significant role in shaping household adaptation behaviour. Nevertheless, the modest model fit (Nagelkerke $R^2 = 0.157$) indicates that a substantial portion of the variance in adaptation behaviour remains unexplained, suggesting that unmeasured contextual factors — such as social capital, land tenure, or access to early warning systems, likely contribute additional explanatory power beyond the variables included in this study.

4. Discussion

The findings of our study reveal that several factors influence households' adoption of adaptation measures. Among the factors, awareness of the flood risk map is one of the significant predictor variables. Households with prior knowledge of the flood risk map are more likely to take adaptation measures. This is because such awareness enhances households' understanding of their flood exposure, vulnerability, and the potential impacts specific to their location. Therefore, households tend to take adaptation measures to mitigate the impact of floods. This concept is supported by the work of Ajzen (2011), who suggested that people's actions are influenced by their beliefs, whether they are true or false. This analysis highlights that believing one is living in a flood-prone area has a stronger effect on taking adaptation measures than actually experiencing a flood. The work of Duzí et al. (2017) is also consistent with the above findings, which found that households' perceptions of their flood risk zone influence the adoption of flood risk reduction measures. In contrast, a study in Germany by Kreibich (2011) found that, even though households expressed strong concerns about climate change and flood risk, they were less motivated to take adaptation measures. Instead, socio-economic factors were found to be more significant in the adoption of flood risk reduction measures. It is common that many respondents do not know whether flood risk maps for their community exist or not. This means that people judge flood risk based on their experience and local knowledge rather than on official sources (Siegrist and Gutscher, 2006; Duzí et al., 2017). This may also be the case in the Central Valley of Manipur, where the existence of a flood risk map is generally unknown, and people decide their risk based on their experience and local knowledge.

Interestingly, flood anxiety level was found to be negatively associated with the adoption of adaptation measures. This result contradicts the general perception that a higher anxiety level will eventually lead to taking adaptation measures. One possible explanation is that it may create a sense of fatalism, leading people to believe that floods are unavoidable. It will discourage them from adopting adaptation measures, as they may perceive such efforts as a waste of resources, given the recurring nature of floods. Moreover, flood adaptation is not costless. It requires financial resources, time, and energy (Ndue, 2023). High anxiety may also be linked to limited resources of households. Such households may not adopt adaptation measures even if they want to because of limited resources. Participation in flood preparedness awareness drills/sessions could be another crucial factor. Households participating in awareness drills are more likely to adopt adaptation measures because drills provide practical knowledge and hands-on experience. This helps them understand what actions to take before and during floods. These activities also increase risk perception and preparedness. As a result, households tend to adopt adaptation measures as they become aware of the potential impacts that floods may have on them.

Among socio-demographic variables, income and age are found to be significant predictors. Higher income can lead to greater investment in adaptation measures, as households have additional resources to spend. This study found that higher-income households are more likely to adopt adaptation measures. This finding is in line with the findings of Xu et al. (2018) and Soane et al. (2010), who found that higher income positively influences disaster preparedness behaviour. As noted by Ashenefe et al.

(2017), this may be because households with greater financial resources are able to spend on costly adaptation measures for their structures. However, other studies found that the impact of income on flood adaptation is ambiguous (Ao et al., 2020; Molua, 2009; Baker, 2011; Linnekamp et al., 2011).

Age is also a marginally significant factor (p = 0.07, 90% confidence level), which suggests that older household heads tend to be more likely to adopt adaptation measures. However, the effect is weaker compared to other variables. This result may be due to their greater experience and knowledge about floods. This finding is consistent with previous studies, such as Wang et al. (2026), which suggest that increased adoption may be due to greater experience, knowledge, and decision-making authority within the household. Conversely, Ndue et al. (2023) found that age is negatively related to taking adaptation measures. Households that believe future flood impacts to be greater and much greater are more likely to take adaptation measures than those who are not certain about future flood impacts. The likelihood increases by 2.4 times for 'greater' and 2.8 times for 'much greater' households. This may be because of the broader understanding that perceived risk is a key driver of adaptation, as individuals who recognise higher future threats tend to respond more actively. The findings of this study are in line with the findings of Valois et al. (2023). Notably, direct flood experience over the last five years was not a statistically significant predictor of adaptation behaviour (B = 0.062, p = 0.920). This finding stands in contrast to the work of Mondal et al. (2021), who identified flood experience as one of the main drivers of household adaptation measures in northern Bangladesh, and to broader literature that frames experiential learning as a catalyst for protective action (Bubeck et al., 2012). A plausible explanation in the present context is the near-universal exposure to flooding within the sample: 97% of respondents reported having experienced a flood in the preceding five years. Such a high prevalence leaves almost no variation in the experience variable, making it statistically impossible for the model to detect any association between experience and adaptation, even if a genuine relationship exists. In effect, when an entire community shares the same experience of flooding, that shared experience cannot explain differences in who adapts and who does not. This underscores the importance of moving beyond binary flood experience measures toward more nuanced indicators, such as perceived severity of past flood damage or frequency of inundation, which may better capture variation in experiential risk perception across households.

Gender and education level were also found to be non-significant predictors in this study (p = 0.945 and p = 0.946, respectively). This is at variance with the findings of Rahman et al. (2024), who identified gender and occupation as key determinants of flood preparedness in rural Bangladesh, and with Rehman and Sajjad (2024), who documented gender-differentiated adaptation strategies in West Bengal influenced by caste and social norms. The absence of a gender effect in the present study may reflect the dominant role of male household heads in the sample (76.8%), which limits statistical power to detect gender differences, or it may indicate that in the Central Valley of Manipur, flood adaptation decisions are driven more by household-level financial and institutional factors than by the gender of the decision-maker. Similarly, the non-significance of education suggests that formal educational attainment alone does not translate into greater adoption of adaptation measures; instead, targeted, practical risk-communication channels such as preparedness drills and flood risk maps appear more effective in shaping behaviour than general education levels.

Despite the insightful findings of this research, the study has a few limitations. First, the cross-sectional design precludes causal inference; all associations should be treated as correlational rather than causal. Second, self-reported adaptation measures may introduce recall and social desirability bias. Third, the modest Nagelkerke R^2 (0.157) indicates that unmeasured factors — such as social capital, institutional trust, land tenure, or early warning access — likely explain additional variance. Fourth, the study is geographically confined to the Central Valley; its flat terrain, higher population density, and socio-economic profile differ substantially from the hill districts comprising ~90% of the state, limiting generalisability to mountainous or sparsely populated flood-affected regions. Future studies should extend this inquiry to the hill districts and adopt longitudinal designs to better capture the temporal dynamics of adaptation decision-making.

5. Policy recommendations

The findings of this study underscore the need for an integrated policy framework that addresses the cognitive, institutional, financial, and social dimensions of household flood adaptation in the Central Valley of Manipur. A key priority is strengthening risk communication and awareness. Despite the availability of flood hazard information, awareness of flood risk maps remains extremely low, highlighting the need for MSDMA and district disaster management authorities to disseminate flood risk information in simple vernacular formats and integrate it into village-level planning and community awareness programmes. Risk communication should also move beyond hazard warnings to emphasise practical adaptation solutions, using trusted local leaders, community organisations, and successful local examples to reduce flood anxiety and fatalistic attitudes while strengthening confidence in adaptation measures. Equally important is enhancing community preparedness and institutional capacity. Regular mock drills, evacuation planning, and early warning training should be institutionalised in flood-prone communities, particularly along the Imphal, Iril, and Thoubal rivers. Since participation in preparedness programmes significantly increases the likelihood of adopting adaptation measures, existing initiatives such as the *Aapda Mitra* programme and community outreach activities provide effective platforms for expanding preparedness without creating additional institutional structures. The findings also point to the need for stronger financial and policy support. Existing government programmes, particularly the *Pradhan Mantri Awas Yojana–Gramin* (PMAY-G), should incorporate flood-resilient housing features, while affordable adaptation finance through self-help groups and microfinance institutions could improve access to household-level resilience investments. Such measures would help overcome the financial barriers that currently limit the adoption of resource-intensive adaptations. Effective adaptation policies should further adopt an inclusive and context-specific approach. Communication and outreach strategies should be tailored to different demographic groups, recognising the predominance of older household heads while simultaneously strengthening disaster education among younger generations through schools. Building trust in scientific and government information through sustained engagement with local institutions and community representatives will also be critical for encouraging long-term behavioural change. Finally, climate adaptation should be mainstreamed into local development and disaster planning. Climate projections and forward-looking flood risk information should be systematically incorporated into District Disaster Management Plans and local development programmes such as MGNREGA, promoting resilience-enhancing interventions including drainage improvement, embankment reinforcement, and other flood mitigation measures.

Overall, strengthening household flood adaptation in the Central Valley of Manipur requires a coordinated approach that integrates effective risk communication, community preparedness, financial support, institutional collaboration, and climate-responsive development planning. Such a strategy would not only increase household adaptive capacity but also contribute to building long-term community resilience to recurrent flooding.

6. Conclusion

The present study examines the different household-level flood adaptation measures employed in the Central Valley of Manipur and the factors influencing them. The region is historically prone to flooding, and the findings reveal that low-cost, easily accessible measures are widely implemented, while more resource-intensive and long-term measures are less adopted, mainly due to financial constraints. The analysis reveals that a combination of socio-economic, psychological, and informational factors shapes adaptation behaviour. Awareness of flood risk maps and participation in flood preparedness drills significantly enhance adaptive capacity, underscoring the importance of effective risk communication and community engagement. In contrast, higher flood anxiety reduces the likelihood of adaptation, suggesting that psychological barriers such as fear and fatalism can hinder proactive responses even among households that recognise their flood exposure. Additionally, higher income and older age are positively associated with adaptation, reflecting the respective roles of financial capacity and accumulated flood experience in shaping household resilience. Overall, the study highlights the importance of promoting citizen-led, bottom-up adaptation approaches. Strengthening awareness programmes, improving access to financial resources, and addressing psychological barriers are essential for enhancing adaptive capacity at the household level. The findings also highlight the need for integrating household-level strategies into broader flood risk management frameworks, including District Disaster Management Plans and existing national schemes such as PMAY-G and MGNREGA. By doing so, policymakers can develop more inclusive, effective, and sustainable adaptation strategies to address the increasing flood risks under changing climatic conditions. The mixed-methods framework and logistic regression approach adopted here offer a replicable model for similar flood-prone alluvial valleys in Northeast India and comparable low-income South Asian settings.

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