The Role Of Climate Forecasts In
Shaping Adaptation Behaviour: Evidence From A Cross-Country Survey

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Abstract

Climate change presents considerable global threats, particularly in regions that are dependent on climate-sensitive livelihoods. While advances in climate forecasting have improved the availability and accuracy of climate information, a persistent gap remains between information access and actual adaptive behaviour. This study investigates the behavioural mechanisms that translate climate forecasts into adaptive action using a cross-country survey of 309 respondents across six countries: India, Kenya, Egypt, Indonesia, Nigeria and Japan. Using quantitative method including descriptive statistics, Spearman's correlation and multiple linear regression, this study examined the roles of Access to Climate Forecast Information (ACF), Trust in Climate Information (TCI) and Climate Risk Perception (CRP) in shaping Climate Adaptation Behaviour (CAB). Descriptive analysis revealed a pronounced perception-action gap: climate risk perception was high (mean = 4.09) while adaptation behaviour remained moderate (mean = 3.53). Regression analysis demonstrated that trust in climate information ($\beta = 0.299$, $p < 0.001$) and access to forecasts ($\beta = 0.179$, $p = 0.003$) were significant predictors of adaptive behaviour, whereas risk perception alone was not statistically significant ($p = 0.275$). These findings carry important implications for designing climate services and evidence-based policy interventions.

Keywords: Climate Adaptation Behaviour; Climate Forecasts; Trust in Information; Risk Perception; Cross-Country Analysis; Climate Policy

1. Introduction

Climate change has become one of the most pressing global challenges as the frequency and intensity of weather-related disasters are said to have increased fivefold over the past 50 years (WMO, 2021). As a result, there is growing emphasis on climate adaptation, which refers to actions that help to reduce vulnerability to the current or expected impacts of climate change (UNDP, 2024).

One crucial tool for supporting climate adaptation is climate forecasting. Although improvements in meteorological sciences and data analytics have greatly increased the accuracy and availability of these forecasts, a wide gap still remains between the provision of climate information and actual changes in the behaviour of individuals. Many individuals either do not use available forecasts or struggle to turn them into meaningful actions. Additionally, a lot of the existing literature has focused mainly on the technical aspects of climate forecasting and information dissemination, with only very few looking at the behavioural aspects, including how people interpret and respond to climate information.

This study, by using a cross-country method, explores how differences in governance systems, cultural contexts, and information distribution networks can affect the use of climate information. By identifying the factors that hinder the translation of available climate information into changes in people's behaviour, this research aims to inform the design of more effective climate services, enhance the development of better communication strategies, and support evidence-based policymaking that supports climate change adaptation.

2. Literature Review

The quick pace of climate change and the rise in extreme weather disruptions has made climate adaptation, a new area of study. Early studies in the literature were primarily concerned with the physical and technical aspects of climate forecasting. Recent studies in the literature have moved the emphasis to the behavioral and institutional aspects of climate forecasting, realizing that the success of climate forecasting also depends on the response of people to climate information. (Ronald W. Rogers, 1975) (Thomas Grothmann & Anthony Patt, 2005) (David Maddison, 2007)

2.1 Global Climate Change and Extreme Events

The intensification of extreme weather conditions has now been established in the scientific community. In fact, the IPCC (2021) has documented that the increase in extreme weather conditions has already started due to the increase in global warming caused by anthropogenic activities. The WMO (2021) has documented that the frequency of weather-related disasters has increased fivefold in the last five decades, with the economic losses increasing sevenfold.

2.2 Climate Adaptation Behaviour: Theory and Empirical Evidence

Climate adaptation is broadly defined as adjusting to the actual or anticipated effects of climate change in order to moderate harm or exploit beneficial opportunities (IPCC, 2022). The Protection Motivation Theory (PMT; Rogers, 1975) offers a particularly relevant lens: motivation to act is a joint function of threat appraisal; encompassing perceived severity and personal vulnerability and coping appraisal; encompassing self-efficacy and response efficacy. PMT explains why individuals who perceive high climate risk may nonetheless fail to adapt if they believe they lack the capacity to respond effectively.

The empirical studies have consistently demonstrated that there is a 'perception-action gap.' Grothmann and Patt (2005) showed that while perception of climate risks is a prerequisite for adaptation, it is not sufficient. In addition to this, coping appraisal also has to be high. In a similar vein, Maddison (2007) demonstrated that despite awareness of climate variability among African farmers, they were not able to cope with climate risks. Moreover, Charlier (2023) demonstrated that when psychological vulnerability is high, adaptation planning does not take place. Thus, it is demonstrated that climate adaptation is a complex psychosocial process.

2.3 Access to Climate Forecast Information

For this, access to information about climate is a necessary first step with adaptive decision making being a prerequisite. Hansen et al. (2007) proved that "informed forecasts significantly enhance adaptive decision-making by farmers and communities that are dependent on local resources." Vaughan and Dessai (2014) highlighted that "climate services must be user-centered." There are barriers, such as digital divides and communication infrastructure, that prevent equal access in developing regions, as noted by the World Bank in 2021.

2.4 Trust in Climate Information

Trust in the source and information has also been identified as a crucial mediator in the relationship between information access and adaptive action. Torres-Torres et al. (forthcoming) established that trust in public environmental agencies was a significant predictor of information-based action on climate projections. Lack of institutional trust arising from governance failures, misinformation, or political bias significantly diminishes the utility of high-quality information in climate projections, no matter how accessible it may be.

2.5 Climate Risk Perception

The perception of climate risks is defined as a subjective evaluation of the probability and damage potential of climate-related harm. High risk perception is a frequent driver of adaptation, though the empirical evidence is much more complex. Under circumstances of high psychological vulnerability, elevated risk perception can result in fatalism rather than coping. This was demonstrated by Charlier in 2023.

2.6 Research Gap

Since most studies are restricted to single-country contexts, it limits the generalisability across diverse institutional and cultural settings in spite of a growing body of literature on climate adaptation behaviour. Few studies simultaneously examine access, trust and risk perception as interacting predictors of adaptation behaviour using comparable cross-national data. This study addresses these gaps through a cross-country survey design across six national contexts; India, Kenya, Egypt, Indonesia, Nigeria and Japan to provide a more holistic and empirically grounded understanding of the behavioural drivers of climate adaptation.

3. Methodology

This research study compares multiple countries quantitatively. The primary data for this research were collected through an online questionnaire administered in Google Forms. The targets of this research study are students, young professionals, agricultural workers, and individuals with other occupations, these targets reside in six countries: Nigeria, Kenya, India, Indonesia, Egypt, and Japan. These six countries were selected to learn if there is significant variation in institutional frameworks, climate vulnerability, and access to digital infrastructure. We used a convenience sampling method and obtained 309 respondents.

The questionnaire consisted of four primary constructs: Climate Adaptation Behaviour (CAB), Access to Climate Forecast Information (ACF), Trust in Climate Information (TCI) and Climate Risk Perception (CRP). Each of these constructs have six items on a five- point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree), and the reliability of this survey is analysed through Cronbach's alpha which confirmed an acceptable internal consistency across all four constructs (α = 0.71- 0.81).

Data analysis was performed in Microsoft Excel and R. Descriptive statistics summarised the demographics profile and distributional characteristics of the four constructs. We use inferential analysis that included Spearman's rank-order correlation to assess bivariate relationships and multiple linear regression to assess the predictive effects of ACF, TCI, and CRP on CAB. Two models were estimated: Model 1 was used only for the three construct predictors, while Model 2 added demographic controls of: age, gender, education, occupation, country and area of residence. Standard regression diagnostics showed that assumptions of linearity, normality, homoscedasticity, and absence of influential outliers were fulfilled. (Figure 1).

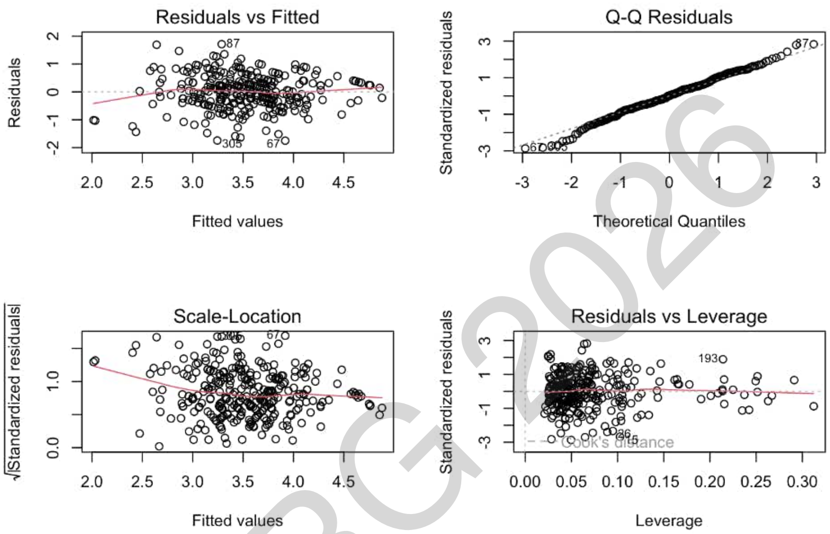

Figure 1: Regression diagnostic plots validating model assumptions

Note: Panels confirm (top-left) linear model fit; (top-right) approximate normality of residuals; (bottom-left) equal variance; (bottom-right) no influential outliers beyond Cook's Distance threshold.

4. Results

4.1 Descriptive Results

Table 1 shows the demographic profile of 309 respondents. The predominance of young people (72.2% aged 18-24) was found in the sample, having nearly equal distribution (50.8% male, 49.2% female) of gender. The largest proportion of respondents (23.3%) belonged to Nigeria, followed by India (17.8%) and then Kenya (17.5%). (45.0%) held a bachelor's degree or were undergraduates and most of the respondents resided in urban regions (65.0%).

Table 1: Demographic characteristics of respondents across six countries (n = 309)

Variable	Category	n	%
Age	18–24	223	72.2
	25–34	50	16.2
	35–44	19	6.1
	45–54	6	1.9
	55+	6	1.9
	Below 18	5	1.6
Gender	Male	157	50.8
	Female	152	49.2
Country	Nigeria	72	23.3
	India	55	17.8
	Kenya	54	17.5
	Indonesia	51	16.5
	Egypt	47	15.2
	Japan	30	9.7
Education	Bachelor's / Undergraduate	139	45.0
	High School or Equivalent	121	39.2
	Master's Degree or Higher	32	10.4
	Vocational / Other	17	5.5
Residence	Urban	201	65.0
	Rural	108	35.0
Total	—	**309**	**100.0**

The descriptive statistics for the four key constructs is showcased in Table No. 2 and Figure 2. The highest mean score (4.09, SD = 0.73) was of Climate Risk Perception (CRP), whereas Climate Adaptation Behaviour (CAB) showcased considerably lower mean (3.53, SD = 0.76). The mean of Access to Climate Forecast Information (ACF) was 3.56 and that of Climate Information (TCI) was 3.53. We observed a negative skewness across all the constructs indicating that responses in general leaned toward higher scores.

Table 2: Descriptive statistics of key constructs (CAB, ACF, TCI, CRP)

Construct	N	Mean	SD	Median	Trimmed	Min	Max	Skew	Kurtosis
CAB	309	3.53	0.76	3.50	3.55	1.0	5.0	−0.43	0.63
ACF	309	3.56	0.85	3.67	3.60	1.0	5.0	−0.56	0.45
TCI	309	3.53	0.79	3.50	3.54	1.0	5.0	−0.25	0.11
CRP	309	4.09	0.73	4.17	4.16	1.0	5.0	−0.95	1.03

Note: CAB = Climate Adaptation Behaviour; ACF = Access to Climate Forecast Information; TCI = Trust in Climate Information; CRP = Climate Risk Perception.

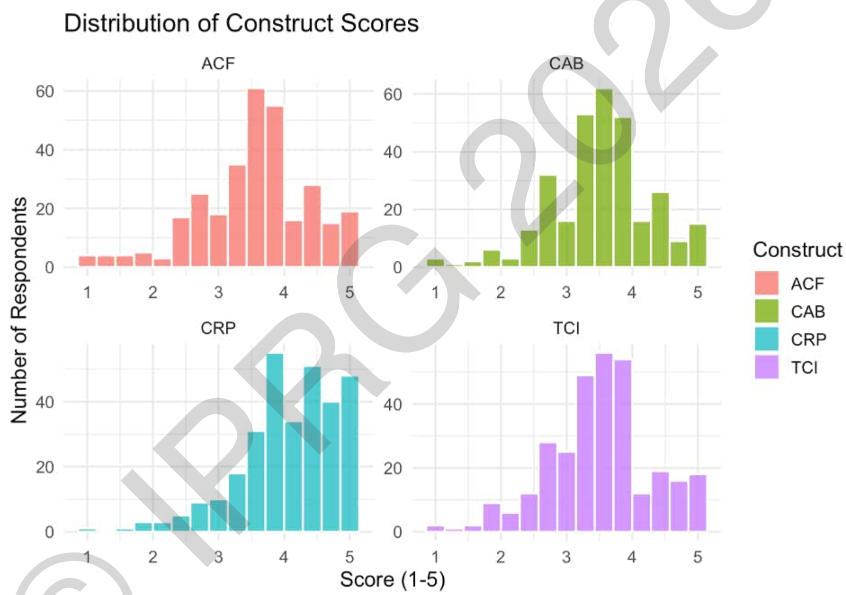

Figure 2: Distribution of composite scores for CAB, ACF, TCI, and CRP

4.2 Cross-National and Demographic Variation

There was an observance of significant differences across all the countries within all four constructs ($p < 0.001$). Higher adaptation behaviour scores were recorded that of India, Kenya and Nigeria while Egypt and Indonesia observed lower scores (Figure 3). There was a slightly higher adaptation behaviour rate in rural respondents than urban respondents, though the pattern was not consistent across all the countries (Figure 4). Both, access and trust was reported higher in male respondents than in female respondents. Nevertheless, no considerable gender differences were found for climate risk perception or adaptation behaviour.

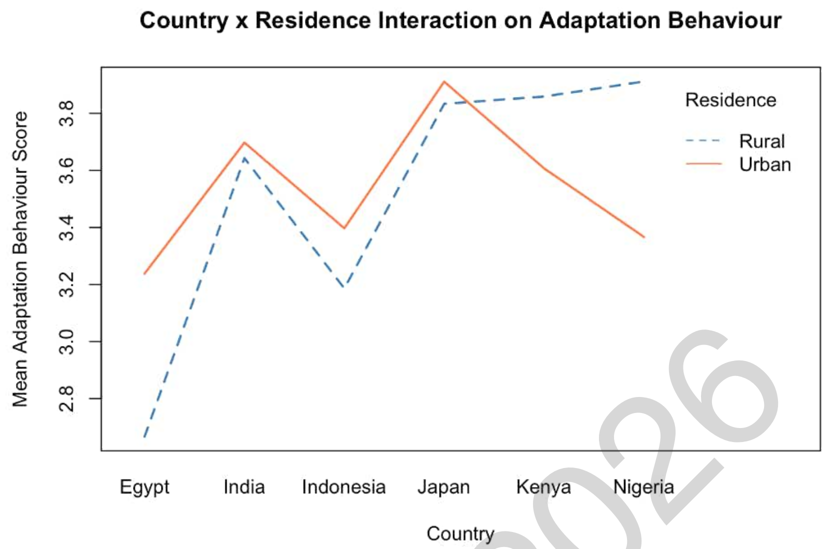

Figure 3: Interaction between country and area of residence on adaptation behaviour

Note: Significant country differences observed ($p < 0.001$). India, Kenya, and Nigeria show higher mean adaptation scores.

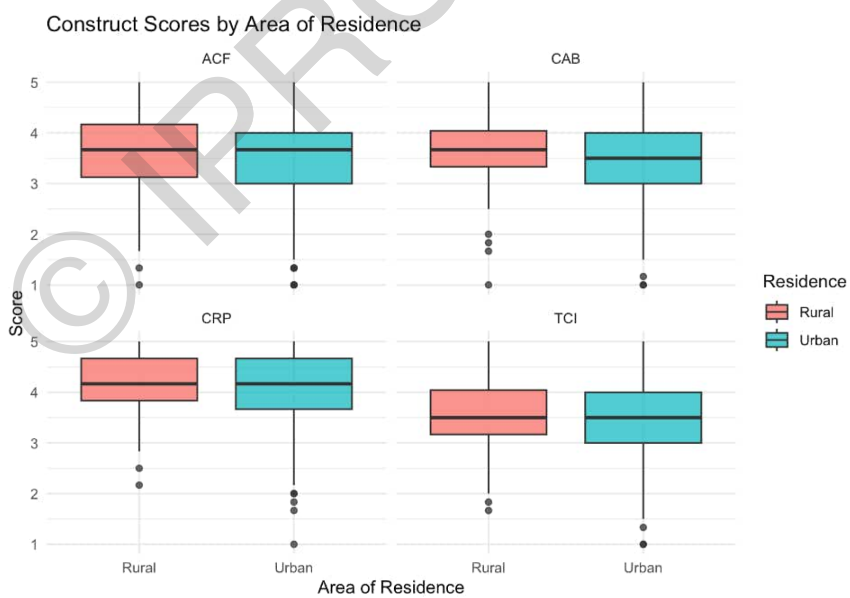

Figure 4: Construct scores by area of residence (Urban vs Rural)

4.3 Correlation and Regression Analysis

There was a positive intercorrelation between all the four constructs (Figure 5). ACF and TCI (r = 0.651) showed the strongest bivariate relationship. The correlation between TCI and CAB (r =

0.459) was stronger than with ACF (r = 0.416), whereas CAB (r = 0.217) was the most weakly associated with CRP.

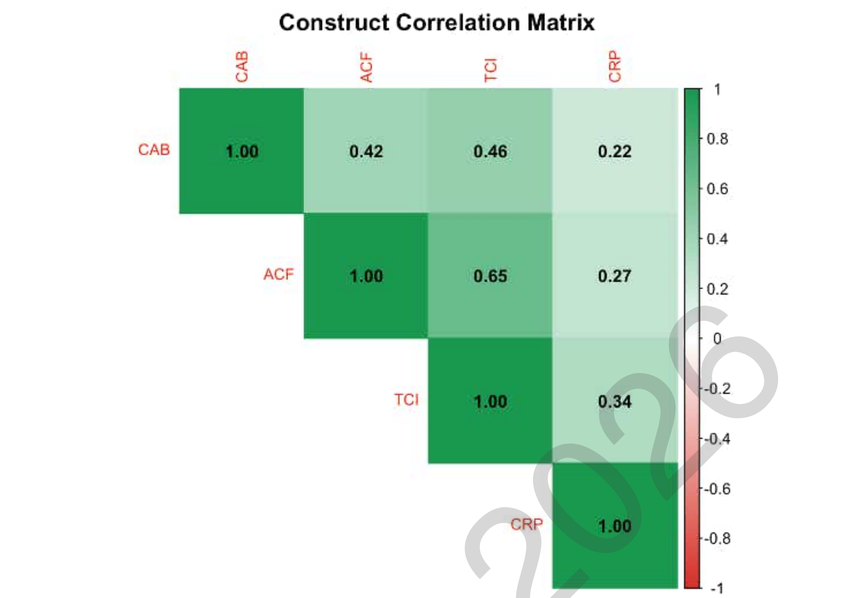

Figure 5: Correlation matrix of key constructs (CAB, ACF, TCI, CRP)

Note: TCI shows the strongest correlation with CAB; CRP shows the weakest.

Table 3: Regression results predicting climate adaptation behaviour (dependent variable)

Predictor	Beta (β)	Std. Error	t value	p-value
Model 1 - Construct Predictors Only (R^2 = 0.237, Adj. R^2 = 0.230, $F(3,305)$ = 31.67, $p < 0.001$)				
Access to Forecast Info (ACF)	0.179	0.060	3.001	0.003 **
Trust in Climate Info (TCI)	0.299	0.065	4.589	< 0.001 ***
Climate Risk Perception (CRP)	0.061	0.056	1.093	0.275 ns
Intercept: 1.588 (SE = 0.246, t = 6.452, $p < 0.001$). Residual SE: 0.671 on 305 df.				
Model 2 - Constructs + Demographic Controls (R^2 = 0.373, Adj. R^2 = 0.327, $F(21,287)$ = 8.133, $p < 0.001$)				
Access to Forecast Info (ACF)	0.296	0.060	4.953	< 0.001 ***
Trust in Climate Info (TCI)	0.285	0.065	4.370	< 0.001 ***
Climate Risk Perception (CRP)	0.112	0.059	1.899	0.059 .
Gender (Male)	−0.149	0.077	−1.936	0.054 .
Country: India	0.577	0.161	3.578	< 0.001 ***
Country: Kenya	0.556	0.162	3.425	0.001 ***
Country: Nigeria	0.594	0.124	4.789	< 0.001 ***

Predictor	Beta (β)	Std. Error	t value	p-value
Country: Indonesia	−0.045	0.161	−0.279	0.781 ns
Country: Japan	0.139	0.177	0.782	0.435 ns
Age (all groups)	—	—	—	ns (all $p > 0.30$)
Education (all levels)	—	—	—	ns (all $p > 0.60$)
Occupation (all types)	—	—	—	ns (all $p > 0.50$)
Residence (Urban)	−0.060	0.081	−0.743	0.458 ns
Intercept: 0.899 (SE = 0.412, t = 2.182, p = 0.030). Residual SE: 0.627 on 287 df. Reference country: Egypt.				
Significance codes: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. $p < 0.10$ ns = not significant				

For Model 1, we get the following observations, ($R^2 = 0.237$, $F(3,305) = 31.67$, $p < 0.001$), and there was a significant prediction of CAB by both, TCI ($\beta = 0.299$, $p < 0.001$) and ACF ($\beta = 0.179$, $p = 0.003$). CRP was found to be statistically insignificant ($\beta = 0.061$, $p = 0.275$). For Model 2, ($R^2 = 0.373$, $F(21,287) = 8.133$, $p < 0.001$), the relationships remained robust even after the addition of demographic controls. India showed significant country-level effects ($\beta = 0.577$, $p < 0.001$), Kenya ($\beta = 0.556$, $p = 0.001$), whereas Nigeria was ($\beta = 0.594$, $p < 0.001$) relative to Egypt. Area, age, education and occupation of residence were statistically insignificant.

5. Discussion

The findings highlight three interrelated dimensions of climate change adaptation behaviour: the persistent gap between perception and action, the crucial importance of trust and the moderating role played by the national context.

The gap between a high perception of climate risk (mean = 4.09) and moderate adaptation (mean = 3.53) confirms the well-documented gap between perception and action within the framework of the PMT model (Rogers, 1975). This gap reflects a failure in the assessment of adaptive capacity: respondents certainly perceive climate risk as serious but do not believe in their own ability to cope with it. The findings of Charliers (2023) which suggest that increased psychological vulnerability can hinder adaptive planning, support this interpretation.

Trust in climate information emerged as the most important predictive factor for adaptation behavior in both models ($\beta = 0.299$; $\beta = 0.285$), which is consistent with the studies by Torres-

Torres et al. (forthcoming) and with the more general theory on source credibility. It is important to note that this effect persisted even after controlling for the variables of country, gender, age, educational level and occupation, indicating that trust is a significant mechanism in its own right. Model 2 showed a significantly stronger effect proving access to forecast information as being significant with regression coefficients being 0.179 and 0.296, suggesting the amplification of its influence when heterogeneity is taken into account contextually. On the whole, improving digital infrastructure, last-mile distribution and communication tailored to the local context are just as important as awareness campaigns, these results showcase.

Significant country effects for India, Kenya and Nigeria compared with Egypt suggest that institutional frameworks, governance structures and community-based networks influence adaptation behavior to a greater extent than individual-level predictors. Universal approaches should not be something on which policymakers should rely and the adaptation must be context-specific. The assumption that awareness-raising measures alone are sufficient is called into question by the very fact that risk perception is not a significant predictor in itself. Trust, access and coping capacity must be addressed simultaneously through taking effective measures.

The representativeness and generalizability of the results leads to the suppression of this study as it uses convenience samples. Furthermore, due to social desirability, self-reported Likert scales are susceptible to bias. Longitudinal designs and mixed methods should be utilized in future research to overcome these limitations.

6. Conclusion

The effectiveness of climate forecasts in driving adaptive behaviour relies not only on their availability but also on how they are trusted and accessed by individuals, critically, as this study shows. Though climate risk perception was found to be high across the sample, the behavioural change was not caused independently by it. Instead, the primary drivers of adaptation turned out to be the trust in climate information and access to forecasts. Even across diverse national contexts and a comprehensive set of demographic controls, these findings remained robust.

The assumption that awareness-raising is the primary lever for climate adaptation was dominantly challenged by these results. The building of institutional credibility, improvement of information accessibility, and the designing of communication strategies that strengthen coping appraisal alongside threat salience should be prioritised by policymakers and climate service providers. Context-sensitive policy design rather than universal solutions, as a need, is underscored by differences in the levels of the country.

Longitudinal designs capturing how behavioural responses evolve as climate conditions intensify as well as qualitative studies that explore individuals' trust-formation processes and access pathways should be certain factors to be pursued in future research. Quantitative findings reported here would be complemented by such work and deepen our understanding of the forecast-to-action pathway.

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